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Disruption without Dividend?

How the Digital Divide and Task Differences Split GenAI's Global Impact

Hernan Winkler (IDB), with Paweł Gmyrek (ILO) and Mariana Viollaz (World Bank)

Background paper for the World Development Report 2026:
The Promise of Artificial Intelligence

GenAI’s effects on jobs are measured almost entirely with US data

What we know, and what is missing for developing countries

What we know

- **GenAI does cognitive, non-routine tasks** — the work of educated, well-paid workers. Earlier waves of automation mostly replaced routine work.
- **Experiments show large productivity gains** in writing, coding and customer service (Noy & Zhang 2023; Brynjolfsson et al. 2025).
- **Since ChatGPT, demand is already shifting:** writing and coding vacancies have fallen, and young workers are affected (Demirci et al. 2025; Hampole et al. 2025); sharp decline in international outsourcing to developing countries (Betai and Chen, 2026).

What is missing

- **Most evidence uses US task data (O*NET)** and assumes a job involves the same tasks everywhere.
- **Developing countries differ in three ways:**
  - their mix of occupations
  - their internet access
  - what workers actually do within the same occupation
- **Automation of expert vs basic tasks.** Whether GenAI takes over a job’s basic tasks or its expert ones (Autor & Thompson 2025).

What this paper adds

Three departures from US-based exposure estimates

1

Global microdata

ILO–NASK (2025) task-based index applied to 4-digit occupation microdata: 135 countries, 67% of global employment.

→ Exposure rises with income, mostly through automation risk.

2

The digital divide, worker by worker

Predicted internet access for each worker in 49 countries (43% of global employment).

→ Those who could gain are offline; those at risk are connected.

3

Task content within occupations

PIAAC + STEP for 46 countries: what workers actually do in the same occupation.

→ Standard indices overstate exposure in developing countries.

Closest to Lewandowski, Madon and Park (2025) and Cazzaniga et al. (2024); extends Gmyrek, Winkler and Garganta (2024) from Latin America to the world.

Four findings

1 Exposure rises with income

About 32% of employment is exposed in high-income countries vs 15% in low-income ones. The gap is driven by automation risk (~8% of global jobs); augmentation potential (~17%) is spread more evenly.

2 Small buffer, big bottlenecks

66.9 million of 441.8 million augmentation-ready jobs lack internet access, while jobs at risk of automation are already connected, even in low-income countries.

3 A white-collar bypass

In poorer countries, automation risk falls on a small but strategic set of good formal jobs: the clerical work that brought women and youth into employment elsewhere.

4 Same job, different tasks

Within the same occupation, workers in developing countries do fewer non-routine analytical tasks, so standard indices overstate GenAI exposure there.

Roadmap

PART 1

Measuring exposure

ILO–NASK (2025) index applied to microdata from 135 countries

PART 2

The digital divide

Who is exposed, and who is online to use GenAI

PART 3

Same occupation, different tasks

PIAAC and STEP task data for 46 countries

PART 4

Beyond exposure

Which tasks GenAI reaches: clerical jobs and expertise

PART 1

Measuring GenAI exposure around the world

Methodology Overview

A Human-AI Collaborative Approach to Assessing GenAI Exposure

ILO (2025) combines **worker knowledge**, **expert judgment**, and **AI capabilities** to create validated task-level automation scores that transfer across occupational classification systems

Human Input

1,640 workers score tasks from their occupational groups, grounding assessments in workplace reality

+

Expert Validation

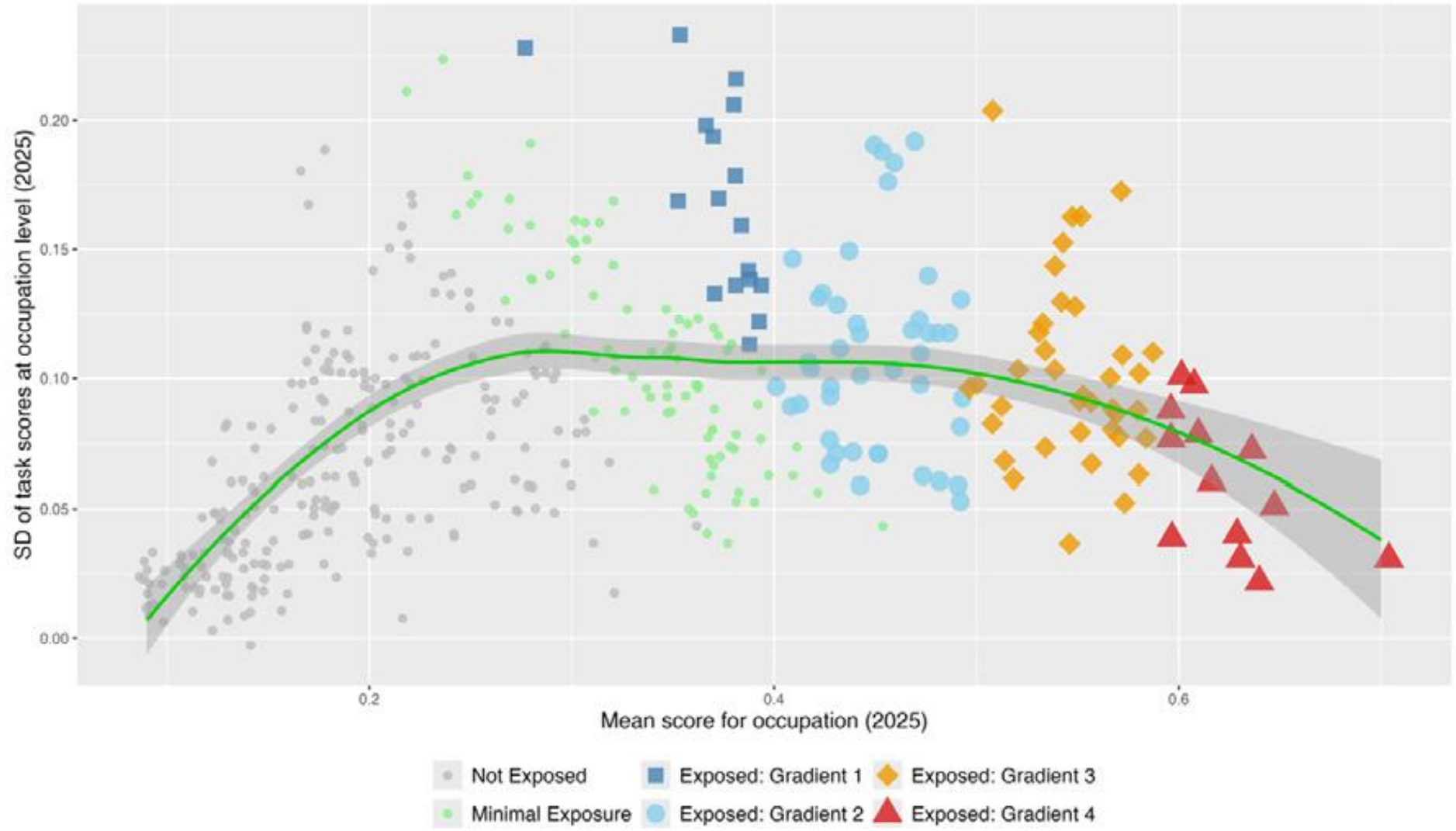
International specialists review and adjust scores through iterative consensus-building

+

AI Scaling

Dual LLM arbitration reconciles inputs and extends predictions to all tasks via semantic similarity

AI Exposure Gradients: ISCO-08 4-digit level occupations



Each point is an ISCO-08 4-digit occupation. Full scores: pgmyrek.github.io/2025_GenAI_scores_ISCO08

From Tasks to Occupations: Exposure Gradients

Classifying occupations using the distribution of task-level scores

Why Move Beyond Binary Categories?

The 2023 study used automation vs. augmentation with a large "unknown" middle category. This was difficult to interpret for policy. The 2025 approach creates a continuous spectrum that better captures how GenAI impacts occupations at varying levels.

Two Key Metrics Per Occupation

μ
Mean task score
Overall exposure level

σ
Std deviation
Task variability

The Classification Logic

High mean + Low SD = Most tasks consistently automatable → Highest risk
High mean + High SD = Some tasks automatable, others not → Transformation
Low mean + High SD = Few tasks automatable with variation → Augmentation

The Six Exposure Categories

GRADIENT 4: Highest — $\mu \geq 0.6, \mu - \sigma \geq 0.5$

High, consistent exposure. Most tasks automatable with little variability.

GRADIENT 3: Significant — $0.5 \leq \mu < 0.6, \mu + \sigma \geq 0.5$

Above-moderate. Some tasks less exposed, but automation potential growin

GRADIENT 2: Moderate — $0.4 \leq \mu < 0.5, \mu + \sigma \geq 0.5$

Mix of exposed and non-exposed tasks. Uneven impact across occupation.

GRADIENT 1: Low — $\mu < 0.4, \mu + \sigma \geq 0.5$

Low overall but high task variability. Some tasks have elevated potential.

MINIMAL — $\mu < 0.5, \mu + \sigma > 0.4$

Low exposure with some moderate-potential tasks. Limited overall impact.

NONE — Otherwise

Most tasks unaffected. Low variability and stable low mean score.

Augmentation, Transformation and Automation Potential: Some Examples

Augmentation Potential: Education Methods Specialists

Tasks (sample)	Automation feasibility
Visiting classrooms to observe teaching techniques and to evaluate teachers performance, and scholastic results obtained;	0.235
Organizing and conducting workshops and conferences to train teachers in new programmes and methods;	0.3
Preparing reports and making recommendations to educational authorities concerning possible changes and improvements in curricula, teaching methods, and other matters.	0.435
Evaluating and advising on contents of courses and methods of examination;	0.485
Developing the structure, content and objectives of new educational courses and programmes;	0.4975
Documenting subjects and courses developed, and evaluating new courses;	0.5975

Automation Potential: Financial Analysts

Tasks (sample)	Automation feasibility
Interpreting data affecting investment programmes, such as price, yield, stability, future trends in investment risks and economic influences;	0.62
Preparing plans of action for investment based on financial analyses;	0.6225
Monitoring economic, industrial, and corporate developments through analysis of information obtained from financial publications and services, investment banking firms, government agencies, trade publications, company sources and personal interviews;	0.635
Analysing financial information to produce forecasts of business, industry, and economic conditions for use in making investment decisions;	0.645

Estimating GenAI Exposure Across Countries

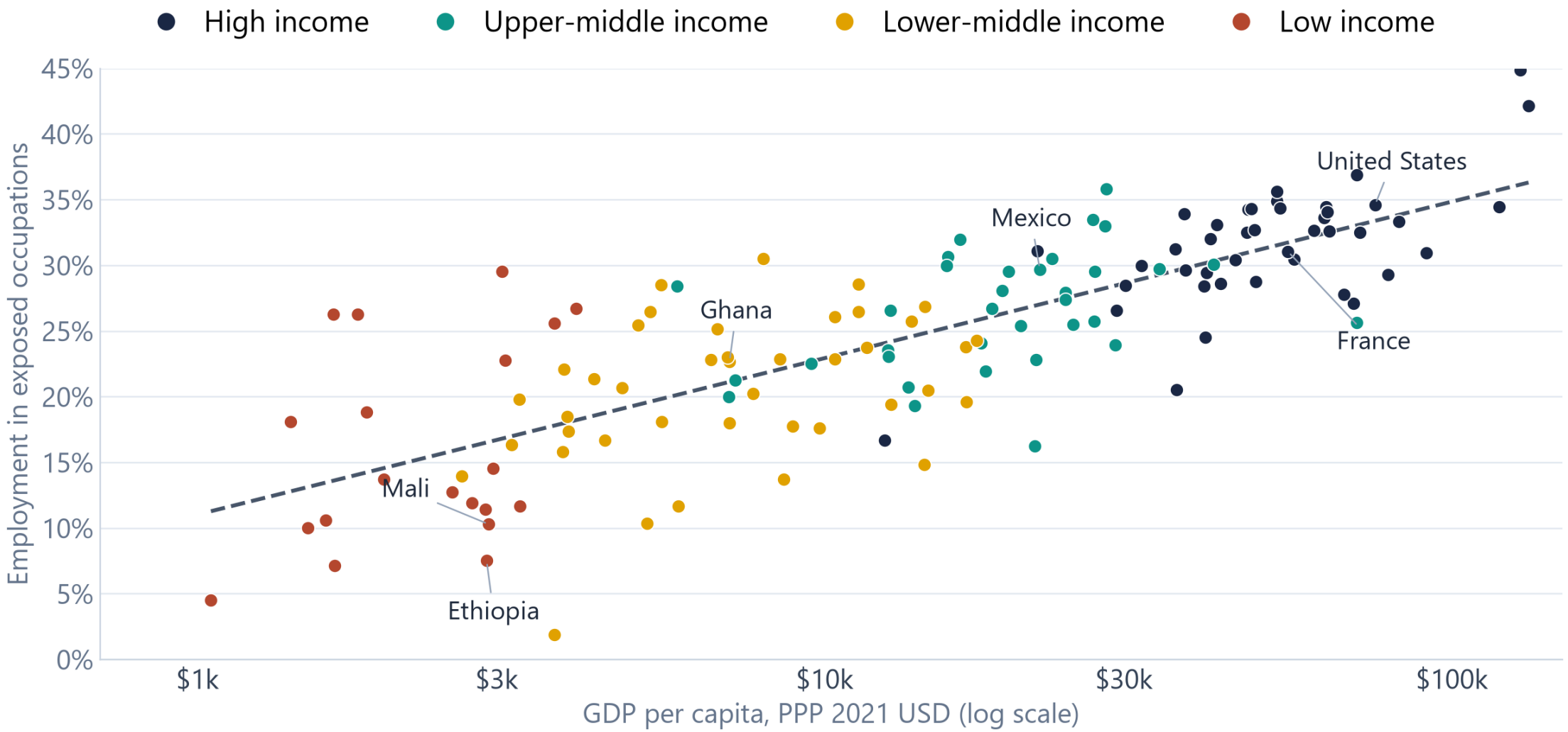
- **Data integration:** Combine multiple sources with ISCO-08 occupational data to measure GenAI exposure.
- **Microdata (26 countries with 4-digit ISCO):**
  - **LABLAC/SEDLAC (7):** Latin America labor force surveys
  - **WAEMU (5):** West African countries
  - **PIAAC (6):** Mostly high-income economies
  - **GLD (8):** Developing countries worldwide
- **Microdata** (23 countries with 1-, 2- and 3-digit data)
- **Expanded coverage:** Add ILOSTAT employment tabulations (2-digit) for countries lacking microdata

→ **135 countries** covering **67% of global employment**.

Estimating GenAI Exposure Across Countries

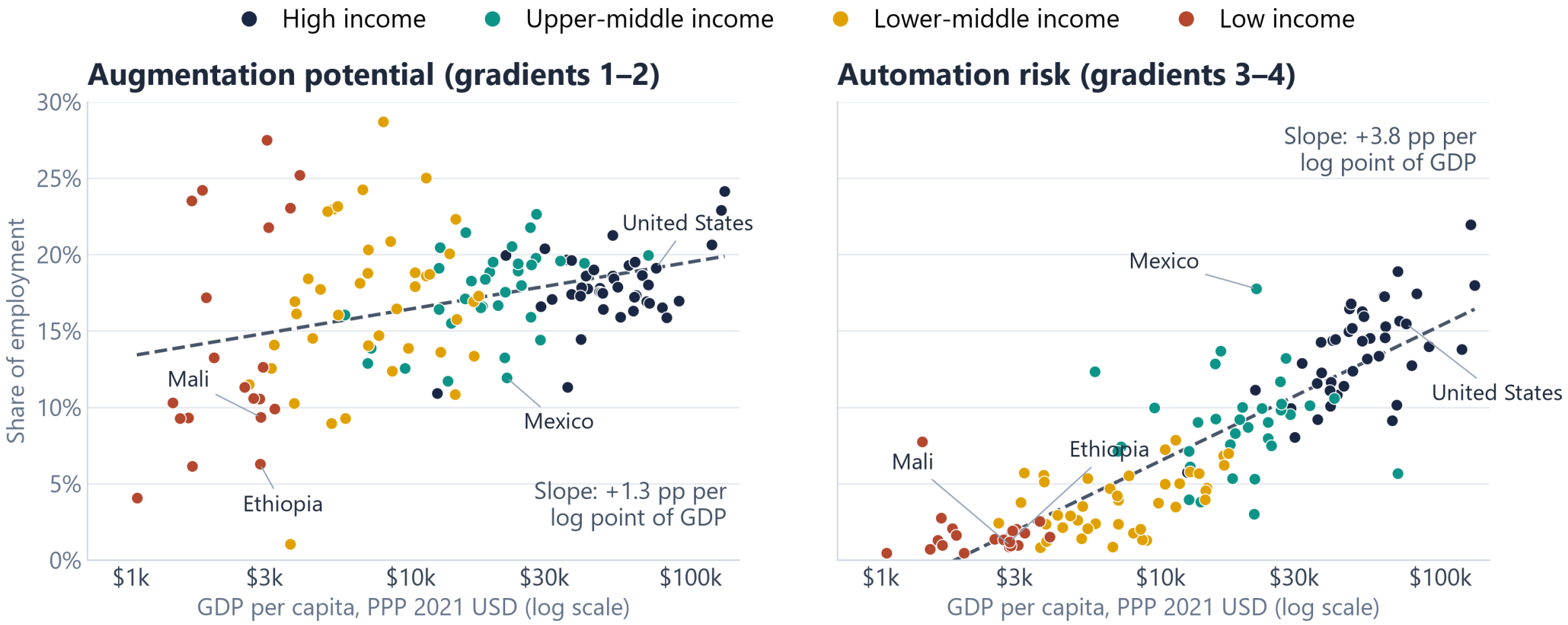
- Merge 4-digit occupation microdata with GenAI exposure index.
- Compute aggregated exposure at 1-, 2-, and 3-digit ISCO levels.
- **Imputation:** For countries without 4-digit data, use a **kNN algorithm** to select a similar “donor” country based on:
  - Employment shares by occupation
  - Internet penetration
  - Region classification
  - Log GDP per capita (PPP)
  - Log population
- Impute exposure at the **highest available granularity (occupation level)**.

Richer countries have more of their jobs in GenAI-exposed occupations



Each dot is a country (137). Exposed = employment in any exposure gradient (1–4). Dashed line: linear fit.

Automation risk rises with income three times as fast as augmentation potential



Same vertical scale in both panels. Each dot is a country (137); dashed line: linear fit.

PART 2

The digital divide: who can actually use GenAI?

Modeling Internet Access for GenAI Exposure

Goal: Adjust national GenAI exposure estimates using individual-level internet access.

Data Sources:

- 32 surveys from **SEDLAC, WAEMU, PIAAC** with household/individual internet data
- Microdata harmonized across surveys
  - SEDLAC & WAEMU: household-level internet
  - PIAAC: individual-level, multiple dimensions (device ownership, usage frequency)
  - Chile bridge**:** PIAAC measure (ICTEVER) matches SEDLAC (97.2% vs 97.4%)

Modeling Approach & Application

Modeling:

•Logistic regression (logit) to predict probability of internet access:

$$internet_{ic} = \beta_0 + \sum_{k=1}^{K} \beta_k * X_{k,ic} + \varepsilon_{ic}$$

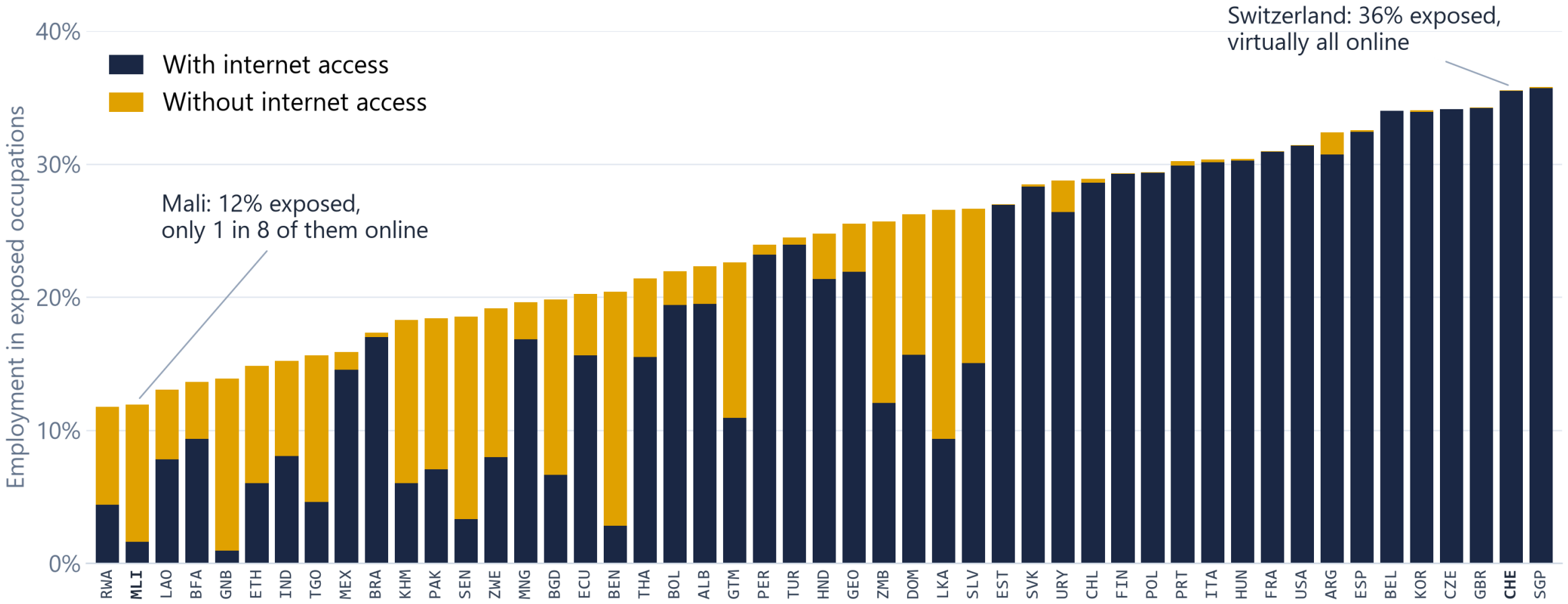
Individual-level predictors:

- Gender, age group (16–65, harmonized with PIAAC)
- Education (none, primary, secondary, tertiary)
- Occupation (1-digit ISCO08) & industry sector (10 GLD categories)

Country-level predictors:

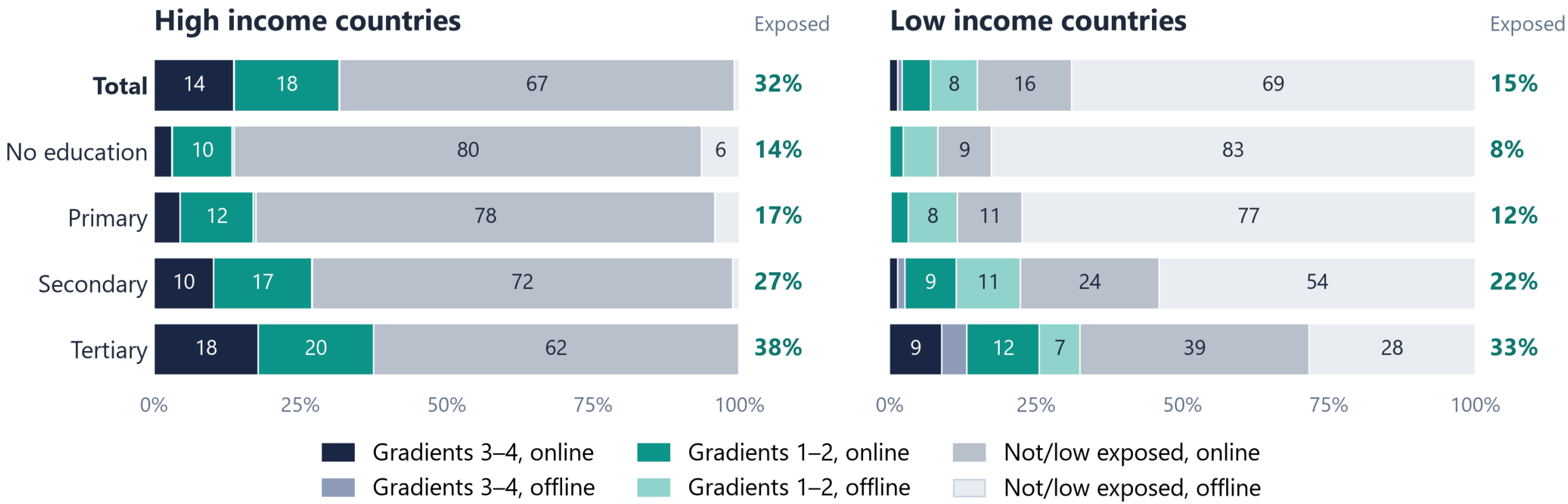
- Internet penetration, electricity access, urbanization, mobile subscriptions, GDP per capita (PPP)
- Interactions terms
- Lasso regularization for variable selection and to prevent overfitting
- Threshold for internet access: **66% probability → internet = 1**
- Predictive accuracy: **83% correct**

Internet access steepens the link between GenAI exposure and income

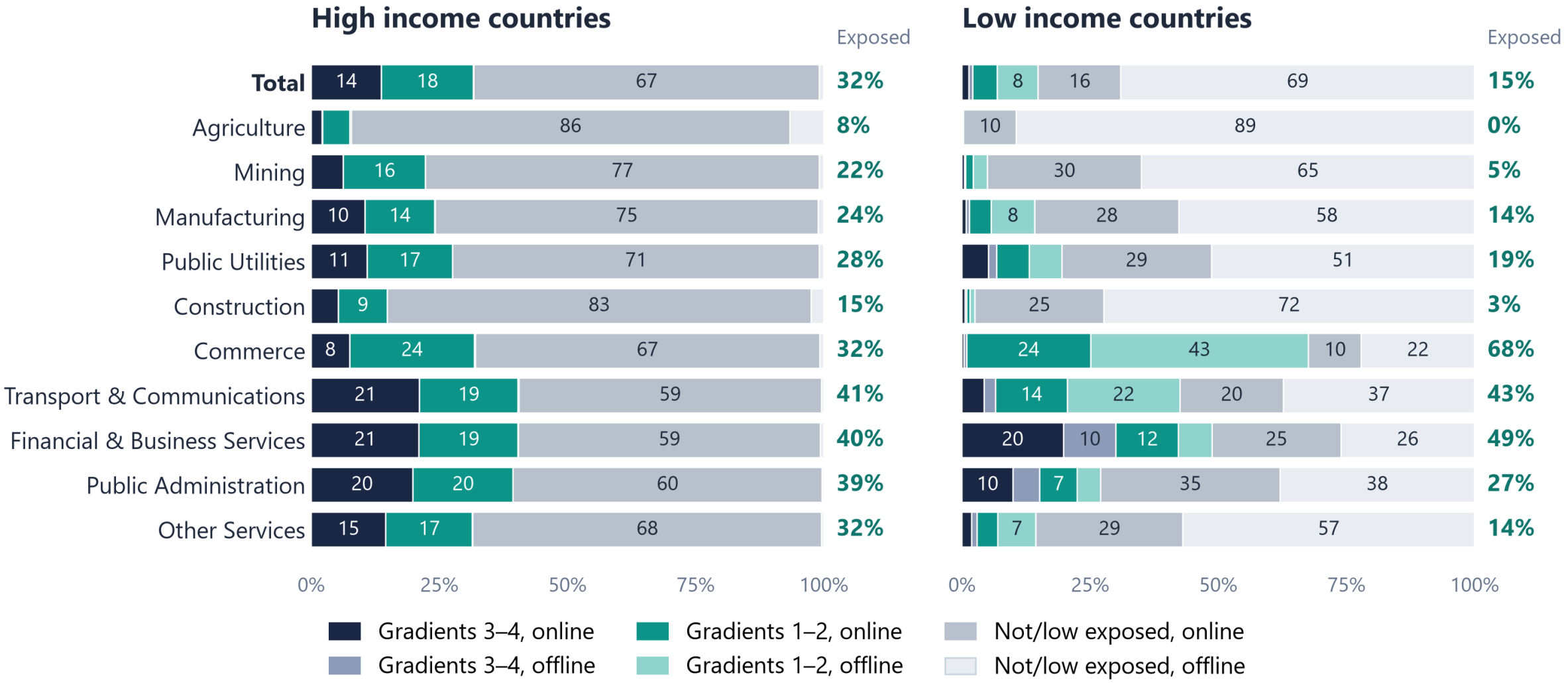


Each bar is a country (49): share of employment in exposure gradients 1–4, split by internet access (observed where surveys ask; predicted otherwise). Paper Figure 3.

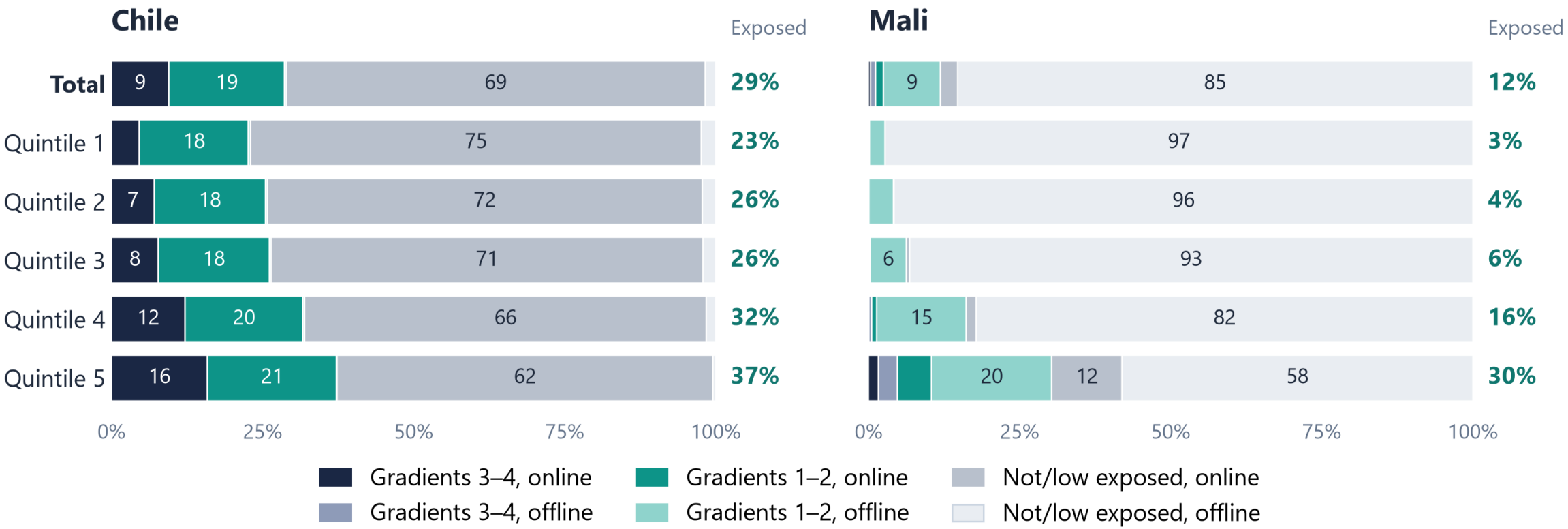
GenAI exposure rises with education in rich and poor countries alike



In poorer countries, the digital divide limits augmentation in retail



Jobs susceptible to GenAI impact tend to be concentrated within wealthier households.



Senegal and Togo show the same pattern as Mali: about a third of the richest quintile is exposed, against 3–6 percent of the poorest.

PART 3

Same occupation, different tasks

Data Sources for Task Content

Objective: Measure task content across occupations globally (based on Caunedo et al. 2023)

Primary Data Sources:

- **PIAAC (OECD)**
  - Surveys adults 16–65 in 39 middle- & high-income countries
  - Measures workplace task frequency/intensity & cognitive skills
  - Final sample: **31 countries** (most recent data)

- **STEP (World Bank)**
  - Surveys adults 15–64 in urban labor markets of low- & middle-income countries
  - Task-specific questions (binary responses)
  - Final sample: **15 countries**

- **Key Challenges:**
  - Different response scales: PIAAC (granular), STEP (binary)
  - High non-response in STEP (avg. 38% for reading tasks)
  - Solution: Use computer-use questions (identical across surveys, <0.1% non-response)

Aggregation & Standardization

Standardization & Aggregation:

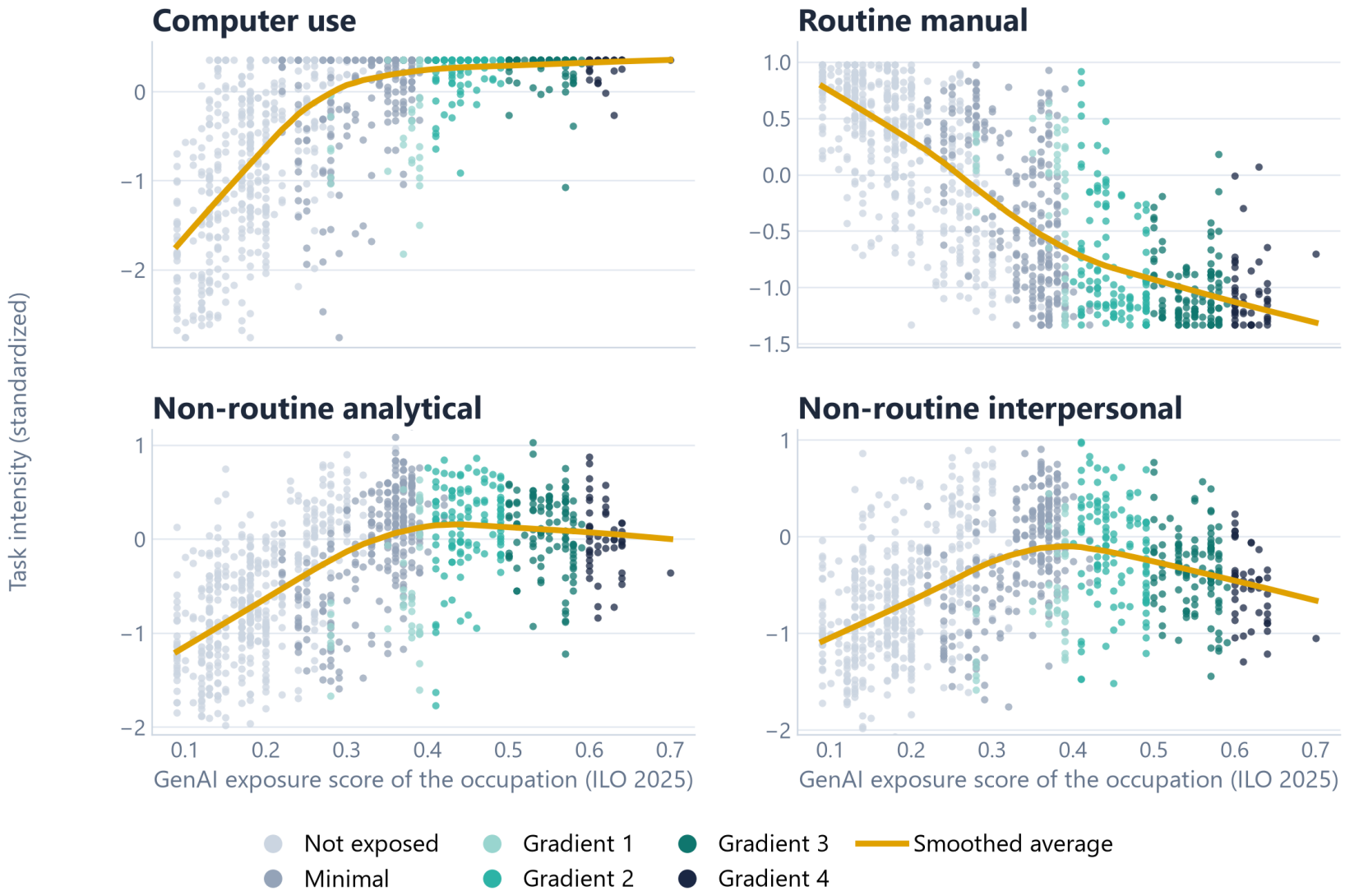
- Standardize tasks using **U.S. worker mean, & SD in PIAAC**
- Combine into 5 broader measures (Autor et al., 2003):
  - **Non-routine analytical (NRA):** reading + creative thinking
  - **Non-routine interpersonal (NRI):** personal interaction + guiding/coaching
  - **Routine cognitive (RC):** structured/repetitive
  - **Routine manual (RM):** controlling machines
  - **Non-routine manual (NRM):** hands/manual tasks

Occupation-Level Measures:

- Weighted average within each occupation-country cell
- 4-digit ISCO-08: 7 PIAAC countries
- 2-digit ISCO: all 46 countries (PIAAC + STEP)
- ✅ Enables **consistent, comparable task-content measures** across diverse countries and occupations

GenAI-exposed occupations use computers more and do fewer routine manual tasks

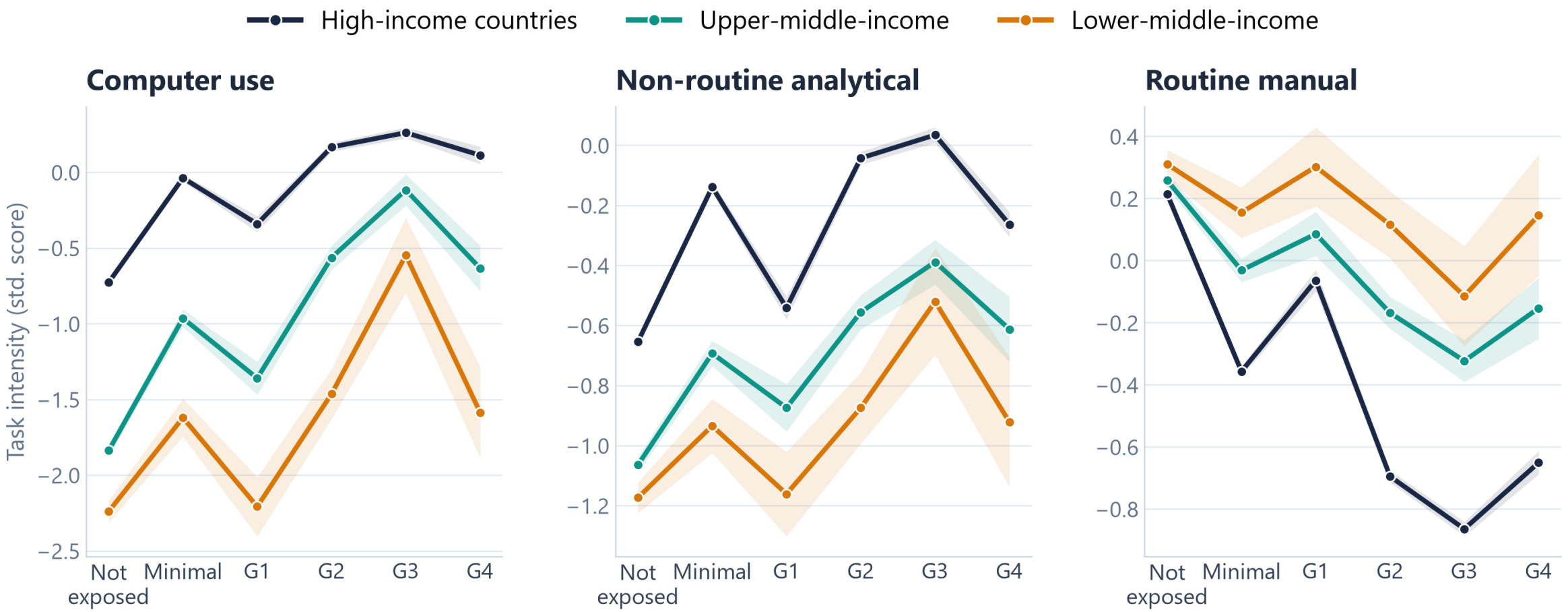
- More exposed occupations use computers more and do less routine manual work
- Analytical and interpersonal tasks peak in the middle of the exposure range



Each dot is a 4-digit occupation in one of 7 PIAAC countries, shaded by ILO exposure gradient. Paper Figure 11.

The same exposure gradient means more analytical, digital work in richer countries

Predicted task intensity by GenAI exposure gradient and country income group (PIAAC and STEP)



Weighted means (employment × GDP per capita) with 95% confidence bands, as in paper Figure 13. Non-routine interpersonal tasks: see paper.

Adjusting Country-Level GenAI Exposure to Task Content Differentials

- We adjust country-level GenAI exposure scores to account for systematic differences in task content across countries.
- We use a generalized additive model (GAM) to account for non-linearities in how each task dimension relates to exposure:

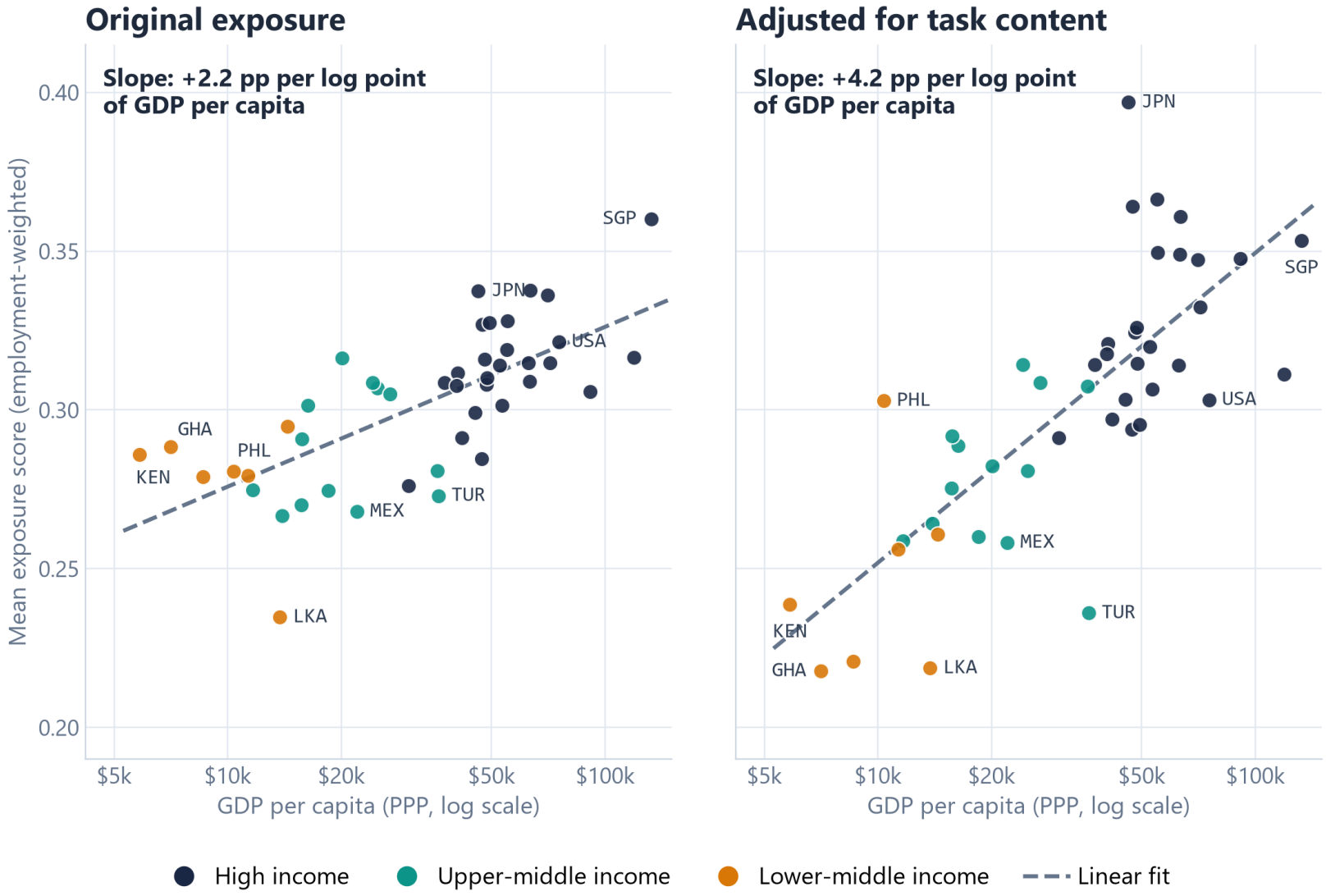
$$\text{Exposure}_{2d}^{(i)} = f_1(\text{CU}_i) + f_2(\text{RM}_i) + f_3(\text{NRA}_i) + f_4(\text{NRI}_i) + \varepsilon_i$$

- Using the fitted model, we generate a new ”adjusted exposure” score for each country–occupation pair at the 2-digit level.
- These predictions are then aggregated to the country level using employment weights to compute a mean adjusted exposure score for each country.

Adjusting for task content steepens the link between exposure and income

- Adjusted exposure rises much more steeply, and more linearly, with income
- Standard indices overstate exposure in developing countries

Each dot is a country (46 PIAAC/STEP countries). Adjusted exposure is the fitted value from a GAM of exposure on computer use, routine manual, analytical and interpersonal tasks. Paper Figure 14.



PART 4

Beyond exposure: clerical jobs and expertise

Companion paper: Gmyrek, Segura, Winkler and Yu (2026), "Generative AI and the Global Redistribution of Expertise." Background paper for the World Development Report 2026.

Which Tasks a Technology Performs Decides Who Gains

The expertise framework of Autor and Thompson (2025)

Expertise

The domain-specific know-how a task requires.

Economically relevant when the goal it enables has market value and the know-how is scarce.

It commands a wage premium and acts as a barrier to entry.

Hierarchical:

air traffic controllers can be crossing guards, but not the reverse — $137,380 vs $36,370 in median US pay.

Narrower than “skill”: it is a property of tasks, not of workers.

Automating an inexpert task

Inside an expert bundle → the barrier rises.

The expertise intensity of the work that remains goes up.

Entry stays restricted; the value of the worker who performs it rises.

In the data: professionals and technicians.

Automating the expert task

The barrier dissolves.

Workers previously excluded can now enter the occupation.

The premium attached to the scarce know-how is competed away.

In the data: clerical support workers.

The same technology applied to the same activity can raise wages in one occupation and depress them in another. Which of the two occurs depends on what else the occupation contains.

Up the income ladder, employment shifts toward expert and exposed jobs

Low income: subsistence crop farmers, farm labourers and shopkeepers dominate, low in expertise and little exposed.

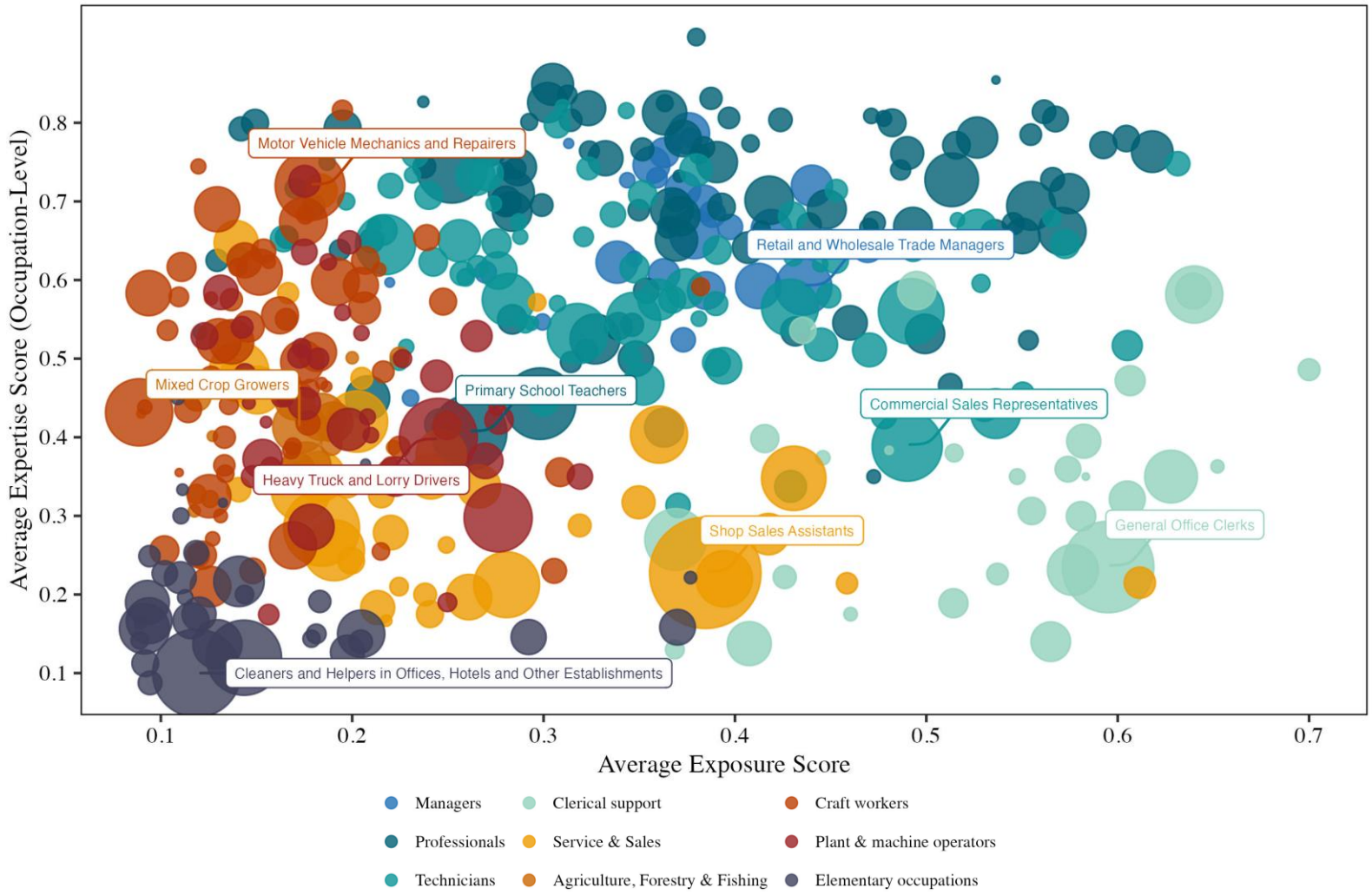
Lower-middle income: farming, crafts and small trade still hold the largest bubbles.

Upper-middle income: the large bubbles begin to move up and to the right.

High income: professionals, technicians, managers and clerical support dominate, including heavily exposed office clerks.

The same occupations meet very different employment structures, concentrating the affected workers in richer economies.

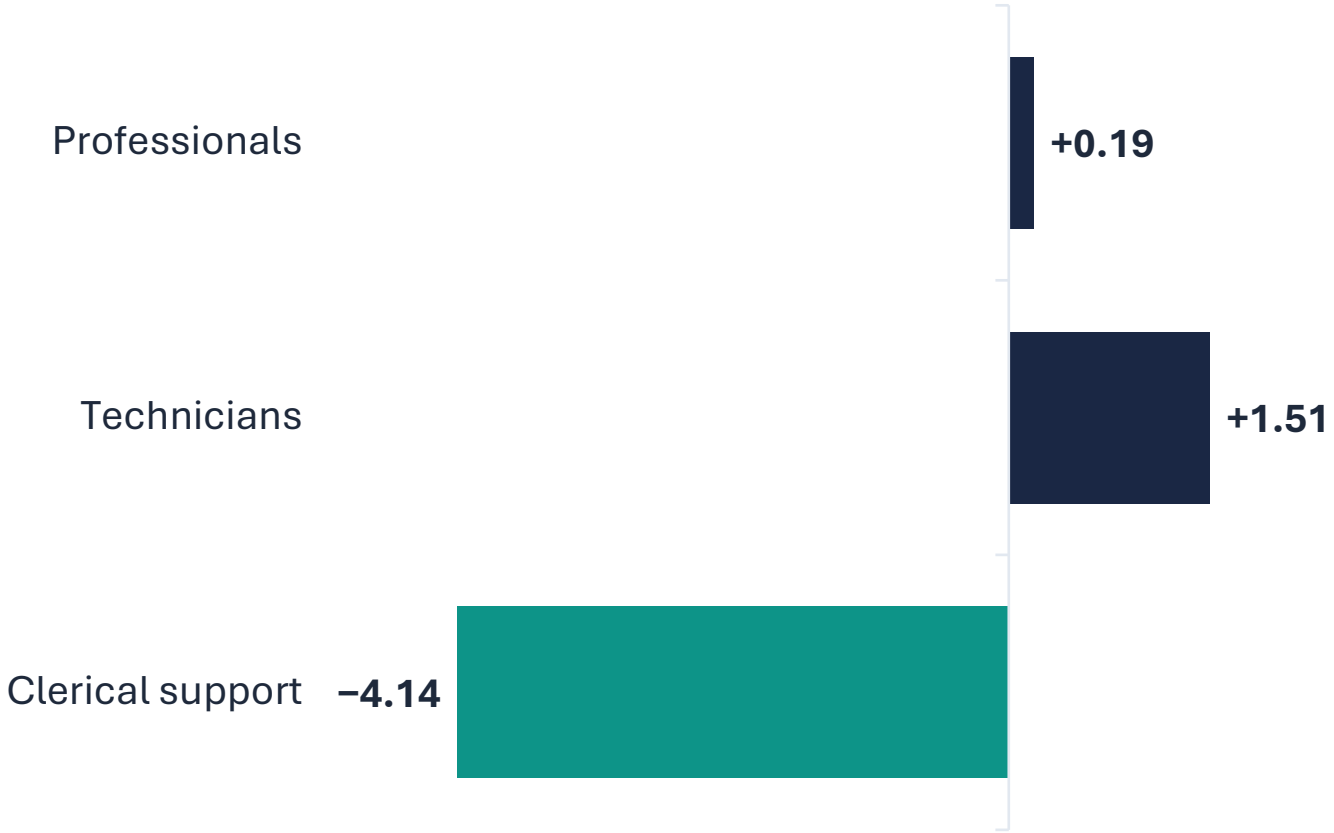
High income



Bubble size: employment within each income group (comparable within, not across, panels). Gmyrek, Segura, Winkler and Yu (2026), Appendix Figure A5.

For clerical workers, GenAI targets the expert tasks, lowering the barrier to entry

Change in mean task expertise (0–100) if exposed tasks were performed by GenAI



Professionals and technicians

Expert tasks are 21 and 15 points less likely to be automatable. GenAI takes the documentation and scheduling; the remaining work becomes more expert.

Clerical support

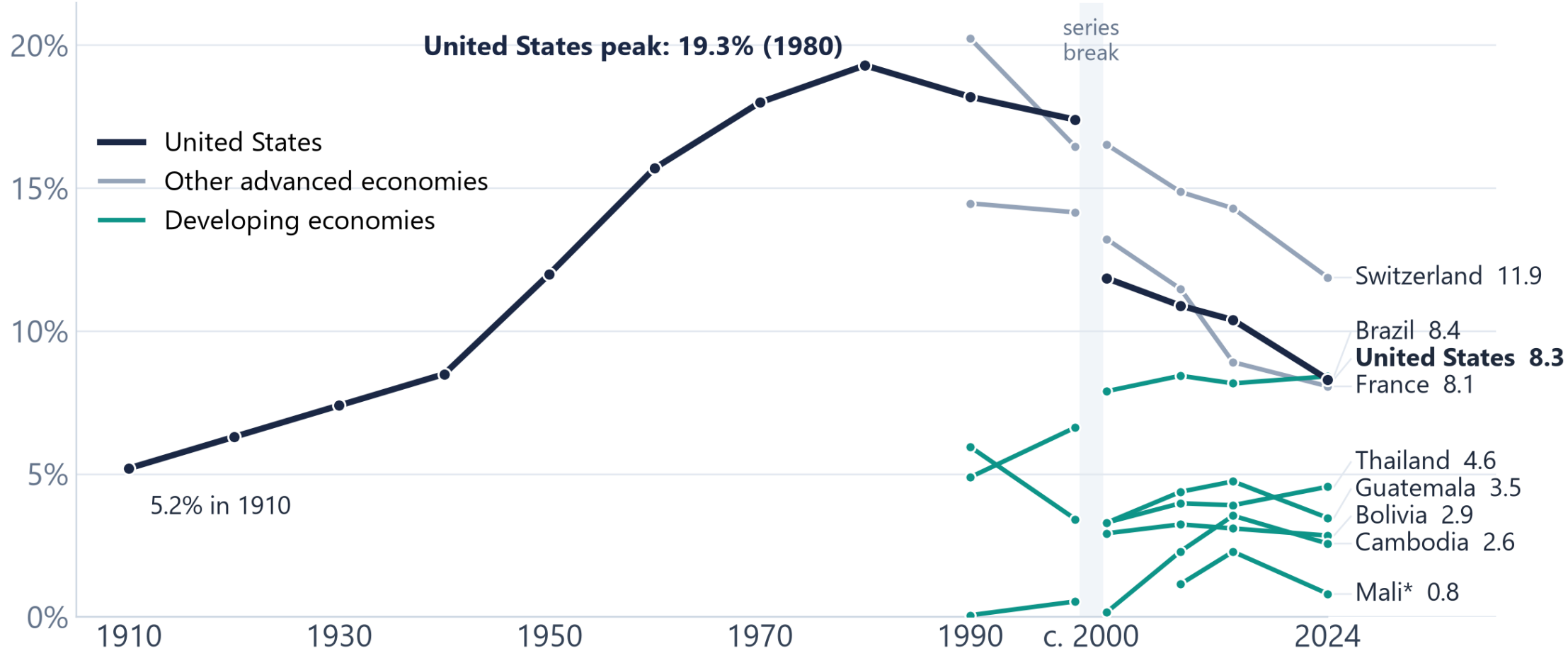
Expert tasks are 12 points more likely to be automatable. Only 8.6% of clerical tasks are expert (vs 82.7% for professionals), and GenAI reaches them.

The white-collar bypass has two margins: fewer clerical jobs, and lower expertise barriers in those that remain.

Source: Gmyrek, Segura, Winkler and Yu (2026), "Generative AI and the Global Redistribution of Expertise," WDR 2026 background paper. Employment-weighted means, 26 countries.

Developing countries may never climb the clerical rung that advanced economies used

Clerical support workers, % of total employment



**Mali: series starts in 2010. Break in 2000–2003: US data for 1910–2000 from Wyatt and Hecker (2006); later data from ILOSTAT (ISCO-08 major group 4).*

Source: Technology, Labor Markets, and Inequality across the Development Spectrum: Reviewing the Evidence.

Conclusions

Exposure rises with development, mainly through automation risk; augmentation potential is spread more evenly across countries.

Small buffer, big bottlenecks: ~67 million augmentation-ready jobs lack internet access, while most automation-exposed workers are already connected. Disruption may arrive before the dividend.

Strategic jobs at risk: in lower-income countries, automation risk is concentrated in a small set of good formal jobs, where fiscal capacity to cushion transitions is weakest.

White-collar bypass: clerical jobs that brought women and youth into work may never fully emerge, and GenAI reaches the expert tasks within them.

Measurement matters: assuming uniform task content overstates exposure in developing countries; country task data such as PIAAC and STEP should inform exposure estimates.

Thanks!

The Informal Buffer

How Labor Market Duality Mediates Automation and AI Exposure in Mexico

Guillermo Lagarda[1,3] Gabriel Marin[2]

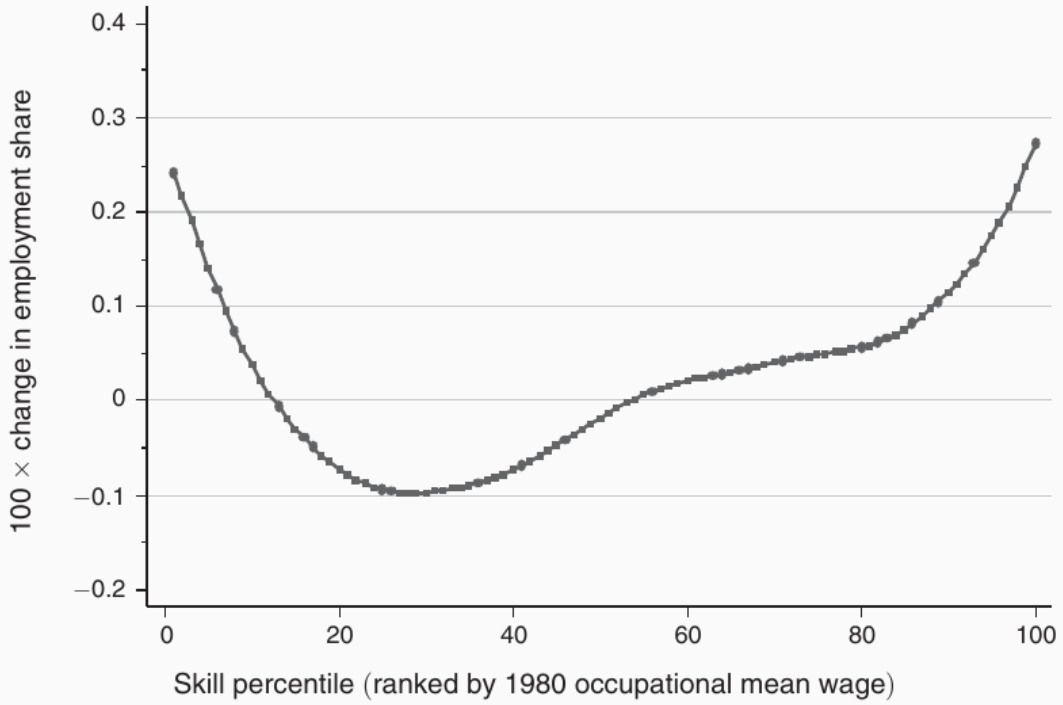
IMF–OECD–PIIE–World Bank Conference, Washington, DC, November 17–18, 2026

[1]Boston University (GDPC) [2]Wharton, University of Pennsylvania [3]Inter-American Development Bank

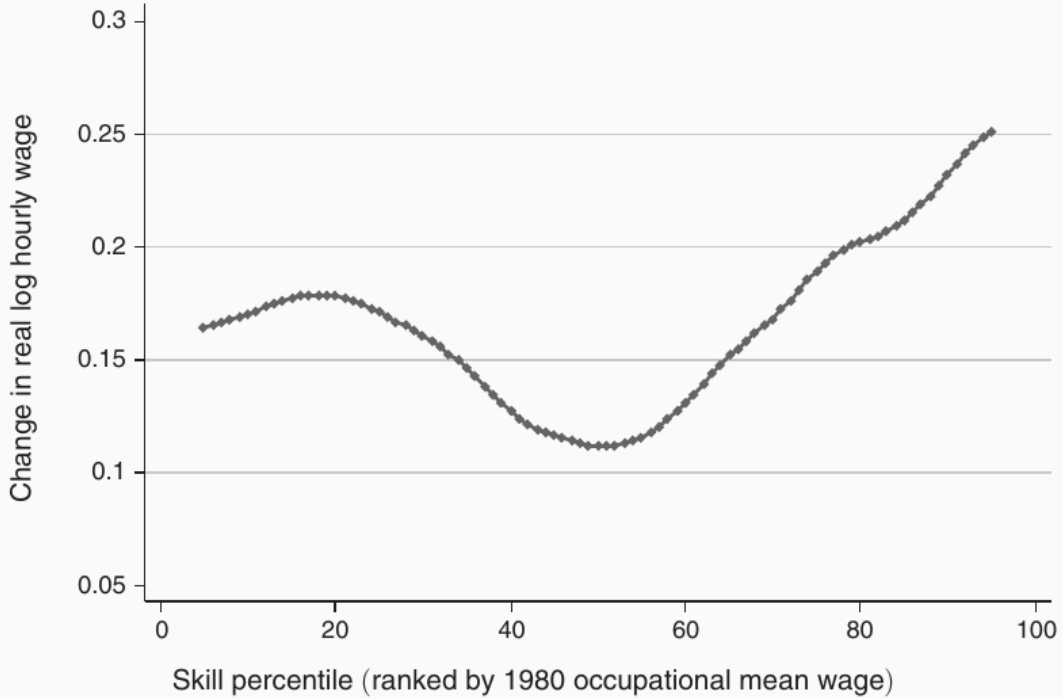
The views expressed are those of the authors and do not necessarily reflect those of the Inter-American Development Bank, Boston University or the University of Pennsylvania.

Routine automation hollows out the middle and polarizes wages

Employment share, US 1980–2005



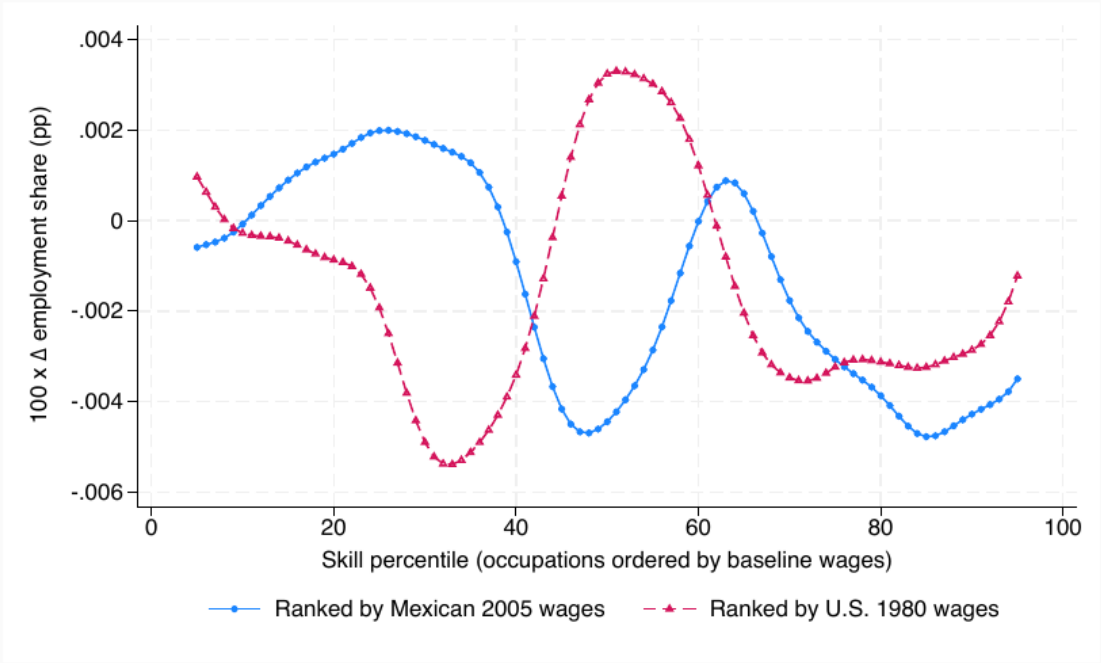
Real hourly wage, US 1980–2005



Source: Autor and Dorn (2013), Figure 1: Census 1980 and ACS 2005, 318 occupations by 1980 mean wage. Also Acemoglu and Autor (2011); Goos, Manning and Salomons (2014).

The formal middle loses jobs, but formal wages do not polarize

Formal employment share, 2005–2019



Formal log monthly wage, 2005–2019



Red ranks occupations by US 1980 wages, as in Autor and Dorn (2013). → all workers → informal

Source: ENOE 2005–2019; occupations ranked by 2005 Mexican mean wage (blue) or US 1980 mean wage (red); LOWESS. Paper Figures 1 and 2 on the paid-subordinate universe; Table 1.

This paper: in Mexico the shock lands on jobs, and self-employment rises

Does labor-market duality shift the incidence of routine automation from wages to jobs?

Formal jobs fall

-0.44 pp

clerical/retail share a year, per 10 points of exposure;
first-stage $F = 74.9$

Formal wages hold

no response

clerical/retail
-0.790 (s.e. 0.492)

Self-employment absorbs

64%

of payroll positions lost reappear as self-employed or unpaid family work

AI: formal clerical falls, services rise

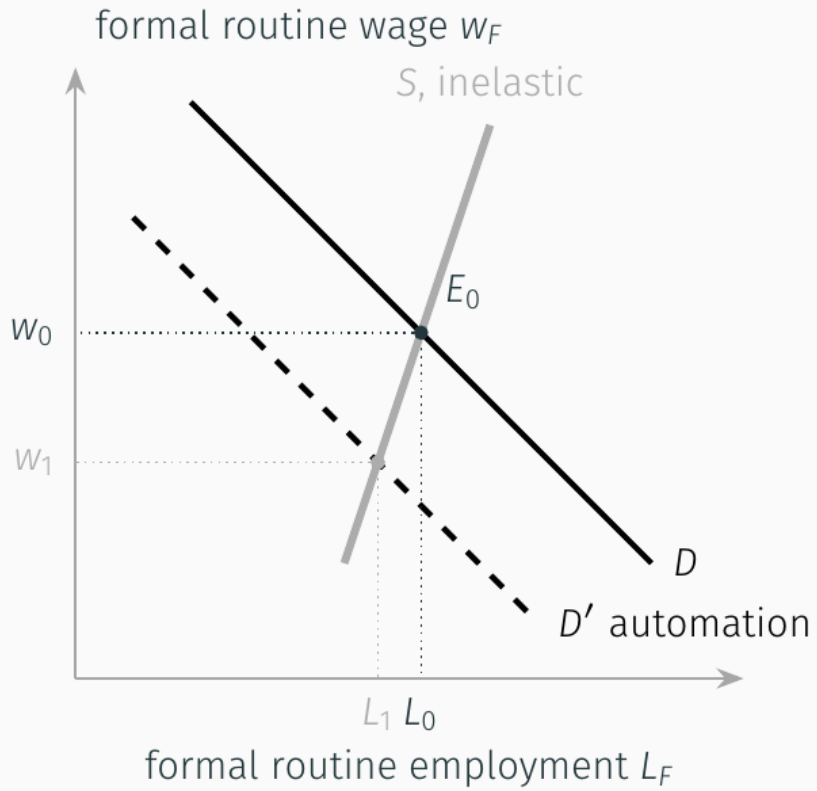
so far

formal clerical/retail share, 2022–25: -0.142 (0.056)
Eloundou et al. task labels

Informality is the buffer · protects formal wages · costs social protection

Source: Local-labor-market 2SLS, Autor–Dorn industry instrument (KP F 74.9, CD 104.1, Hansen J p 0.482, AR p 0.029, 977 LLM-windows); status decomposition (KP 77.9); AI (task-level T measures, industry shift-share; formal first-stage F 15.2, 15.7; informal weak).

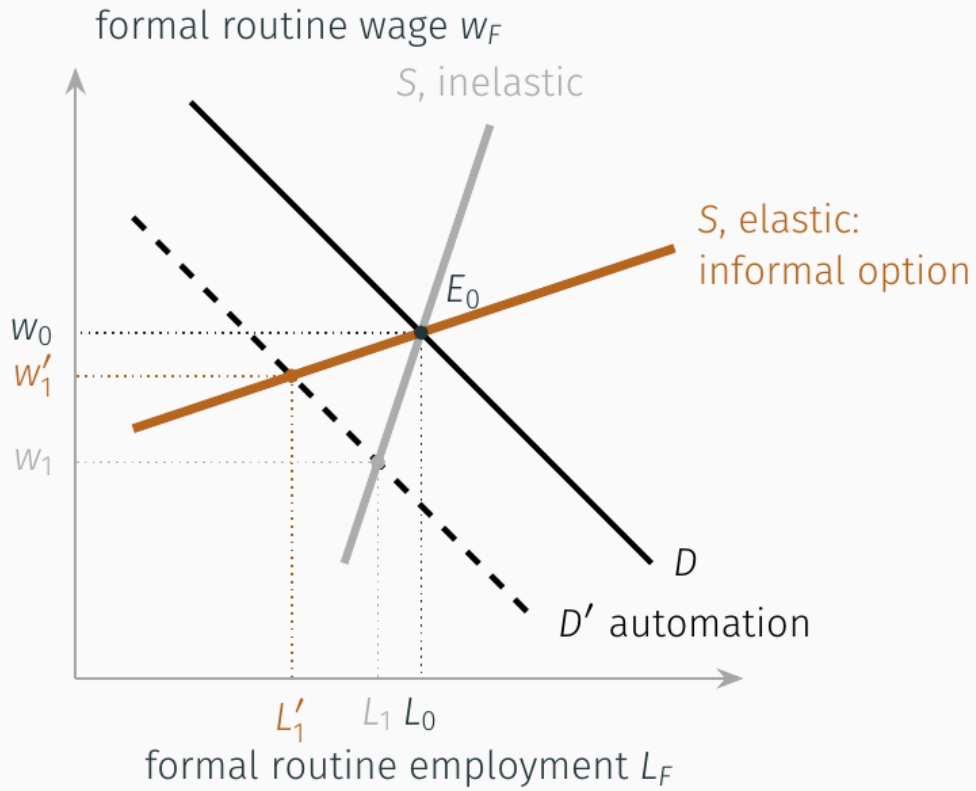
Why formal wages hold: an informal exit turns a wage shock into a job shock



- Automation shifts formal routine demand, $D \to D'$.
- Steep supply: the shock lands in the **wage**, $w_0 \to w_1$.

Predicts: formal jobs fall, formal wages hold, displaced work goes informal, self-employed or unpaid. → full model

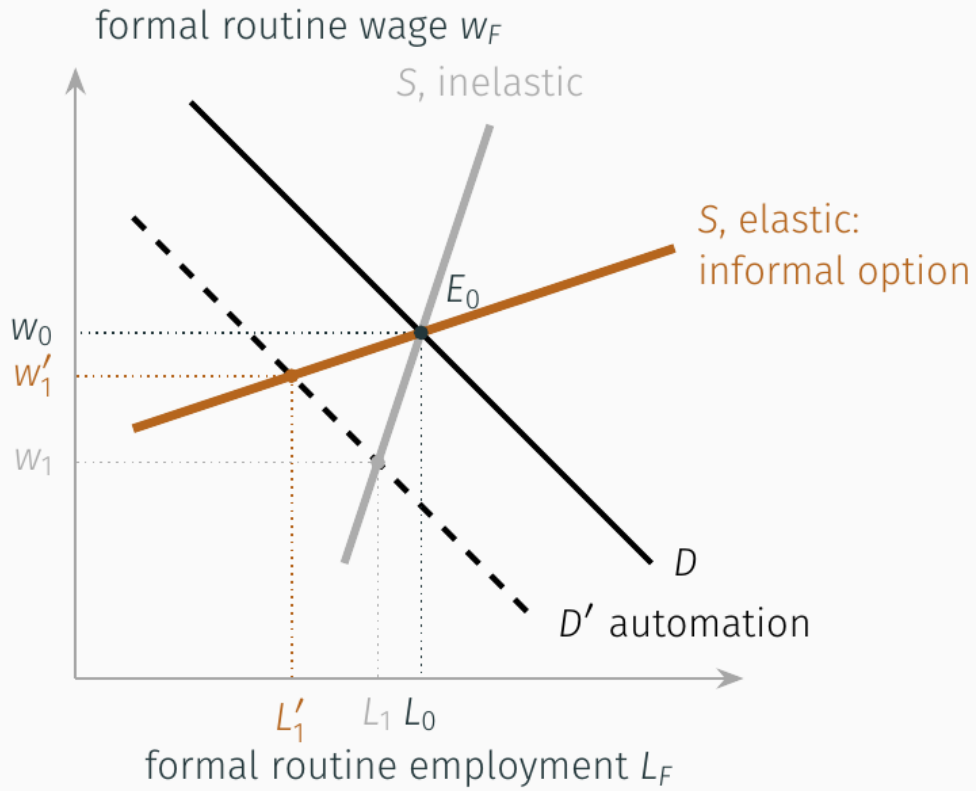
Why formal wages hold: an informal exit turns a wage shock into a job shock



- Flat supply: the shock lands in **jobs**, $L_0 \to L_1'$.
- Flat because workers can go self-employed or unpaid instead.

Predicts: formal jobs fall, formal wages hold, displaced work goes informal, self-employed or unpaid. → full model

Why formal wages hold: an informal exit turns a wage shock into a job shock



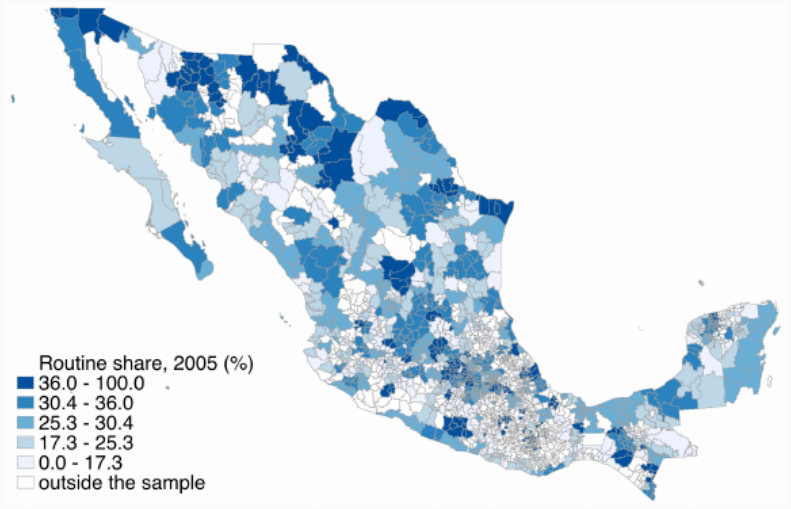
formal if $w_F - d + \varepsilon \geq y$

$$\varepsilon_S = \frac{w_F}{\kappa}(1-\pi)$$

$$B = \frac{\varepsilon_S}{\varepsilon_D + \varepsilon_S}$$

Predicts: formal jobs fall, formal wages hold, displaced work goes informal, self-employed or unpaid. → full model

Exposure is set by each local market's 2005 industry mix



$RSH^F_{\ell,2005}$: routine-exposed share of formal employment by local labor market, 2005 quintiles

Exposure share of the market's formal jobs in routine-exposed occupations, start of window

$$RSH^F_{\ell,t_0} = \frac{\sum_{k \in \mathcal{R}^F} L^F_{k,\ell,t_0}}{L^F_{\ell,t_0}}$$

Instrument 2005 industry shares $\times$ each industry's routine share elsewhere (Autor and Dorn 2013, eq. 22)

$$Z^F_\ell = \sum_i e_{\ell,i,2005}\; R_{i,-\mathcal{S}(\ell),2005}$$

2SLS stacked windows (t_0, t): 2005–10, 2010–15, 2015–19; RSH^F_{ℓ,t_0} instrumented by $Z^F_\ell \times \mathbb{1}\{t = \tau\}$

$$\frac{OG_{g,\ell,t} - OG_{g,\ell,t_0}}{t - t_0} = \beta_g\, RSH^F_{\ell,t_0} + \delta_t + \delta_{S(\ell)} + \varepsilon_{g,\ell,t}$$

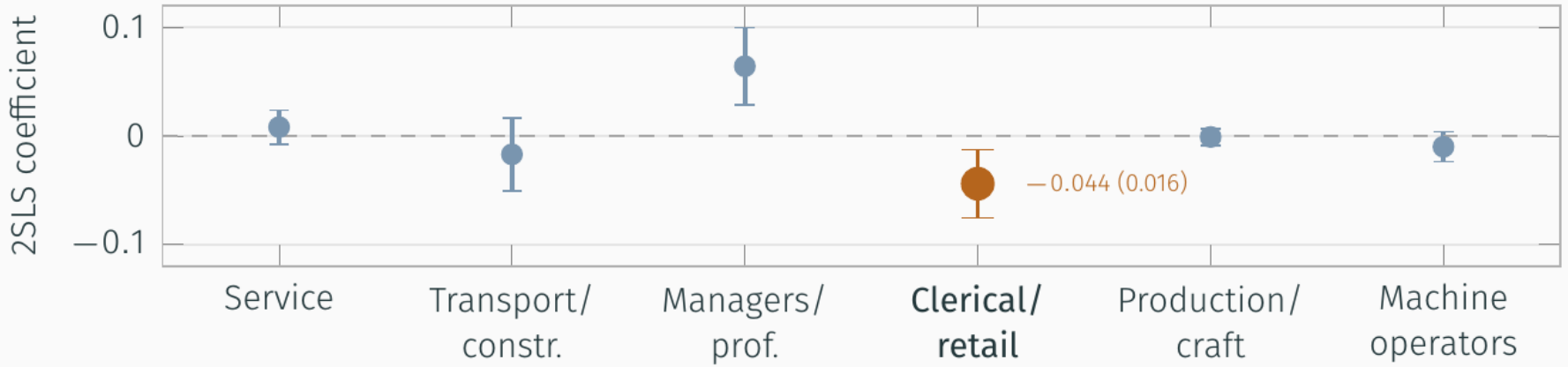
Checks in backup first stage · pre-trends · robustness · Rotemberg

Source: ℓ Banxico local labor market (394 in the sample), g occupation group, $S(\ell)$ modal state, i two-digit industry, OG the group's share of formal employment; start-of-window population weights, 32 modal-state clusters.

Formal clerical/retail jobs shrink where routine exposure was high

$$\frac{OG_{g,\ell,t} - OG_{g,\ell,t_0}}{t - t_0} = \beta_g \, RSH^F_{\ell,t_0} + \delta_t + \delta_{S(\ell)} + \varepsilon_{g,\ell,t}, \qquad RSH^F_{\ell,t_0} \text{ instrumented by } Z^F_\ell \times \mathbb{1}\{t = \tau\}$$

$\hat{\beta}_g$: annualized change in the group's share of formal employment (95% intervals)

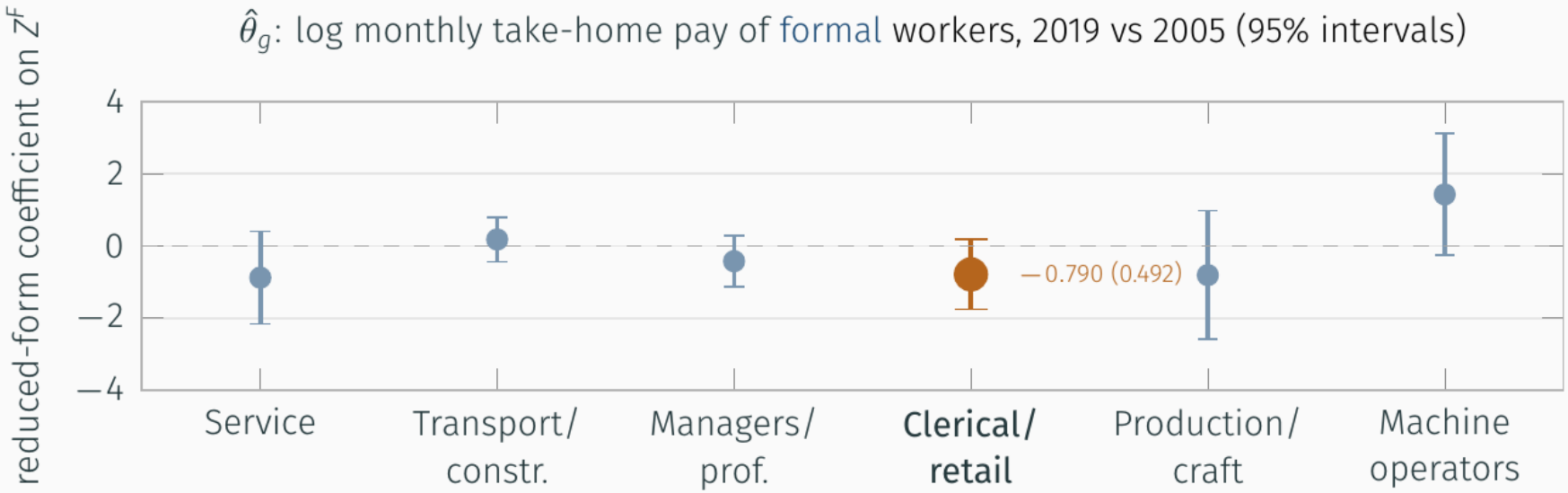


Ten points more of formal employment in routine jobs: the clerical/retail share grows 0.44 pp a year less than in an otherwise similar market.

Source: All regions, stacked windows 2005–10, 2010–15, 2015–19; exposure at the start of each window. KP F 74.9, CD F 104.1, Hansen J p 0.482, AR p 0.029; 977 LLM-windows, 394 markets. → first stage → by region → robustness

Formal wages show no detectable response

$$\ln w_{n,y} = \sum_g \theta_g \, Z^F_{\ell(n)} \, \mathbb{1}\{y = 2019\} \, \mathbb{1}\{g(n) = g\} + \mu_{\ell,k} + \mu_{S,k} + \mathbf{x}'_{n,y}\gamma_y + u_{n,y}, \qquad y \in \{2005, 2019\}$$



Source: Formal paid subordinates, 2005 and 2019; $\mu_{\ell,k}$ market-by-occupation and $\mu_{S,k}$ state-by-occupation effects; $\mathbf{x}$ worker controls by year; labor weights; LLM clusters.

Coefficients per unit of Z^F (SD 0.037). → by region

Self-employment and unpaid family work absorb 64% of the payroll jobs lost

$$y_{k,\ell,t} = \frac{\Delta\,(N_k/\mathrm{Pop})_\ell}{t - t_0} \cdot \frac{\mathrm{Pop}_{\ell,t_0}}{L^F_{\ell,t_0}} = \beta_k\, RSH^F_{\ell,t_0} + \delta_t + \delta_{S(\ell)} + \varepsilon_{k,\ell,t}, \qquad \sum_k \beta_k = 0 \text{ by construction}$$

Where the payroll loss goes: residents 15–64, per routine formal job at baseline, a year (95% intervals)



Source: Residents 15–64, every position; design as on the employment slide. Loss = formal −1.519 (1.094) + informal payroll −0.853 (0.256); self-employed/unpaid 1.518 (0.462). KP *F* 77.9, AR *p* 0.002 / 0.009; 947 LLM-windows; size cut 0.854, winsorized 0.860.

Meet María: a formal secretary covered by IMSS

María

Job secretary (SOC 43-6010)

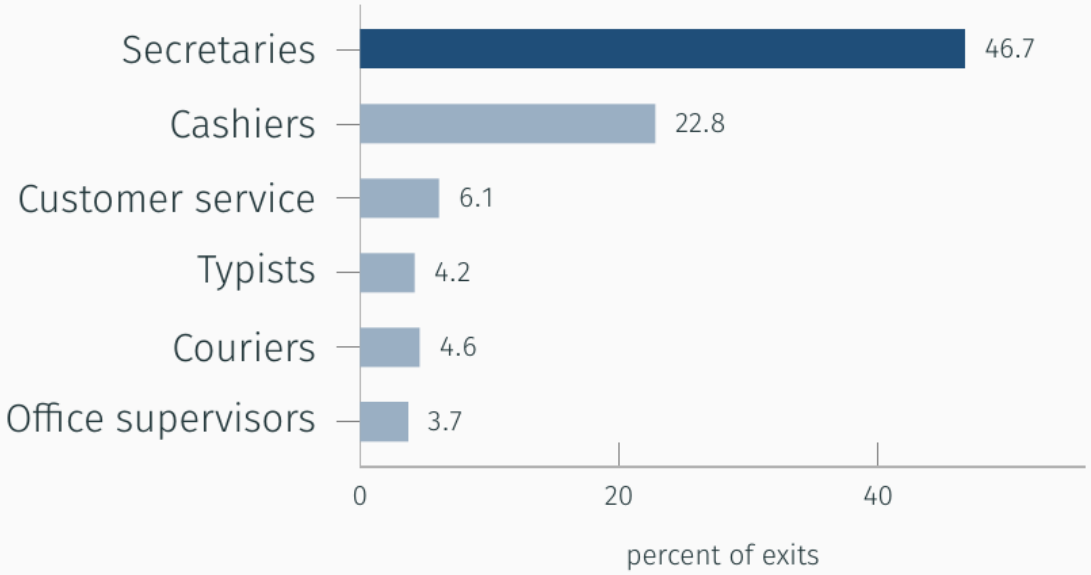
Contract formal, IMSS

Profile 38 years old, high school

Pay 3,618 pesos a month (2005 pesos)

Tasks routine-intensive, top third of formal jobs

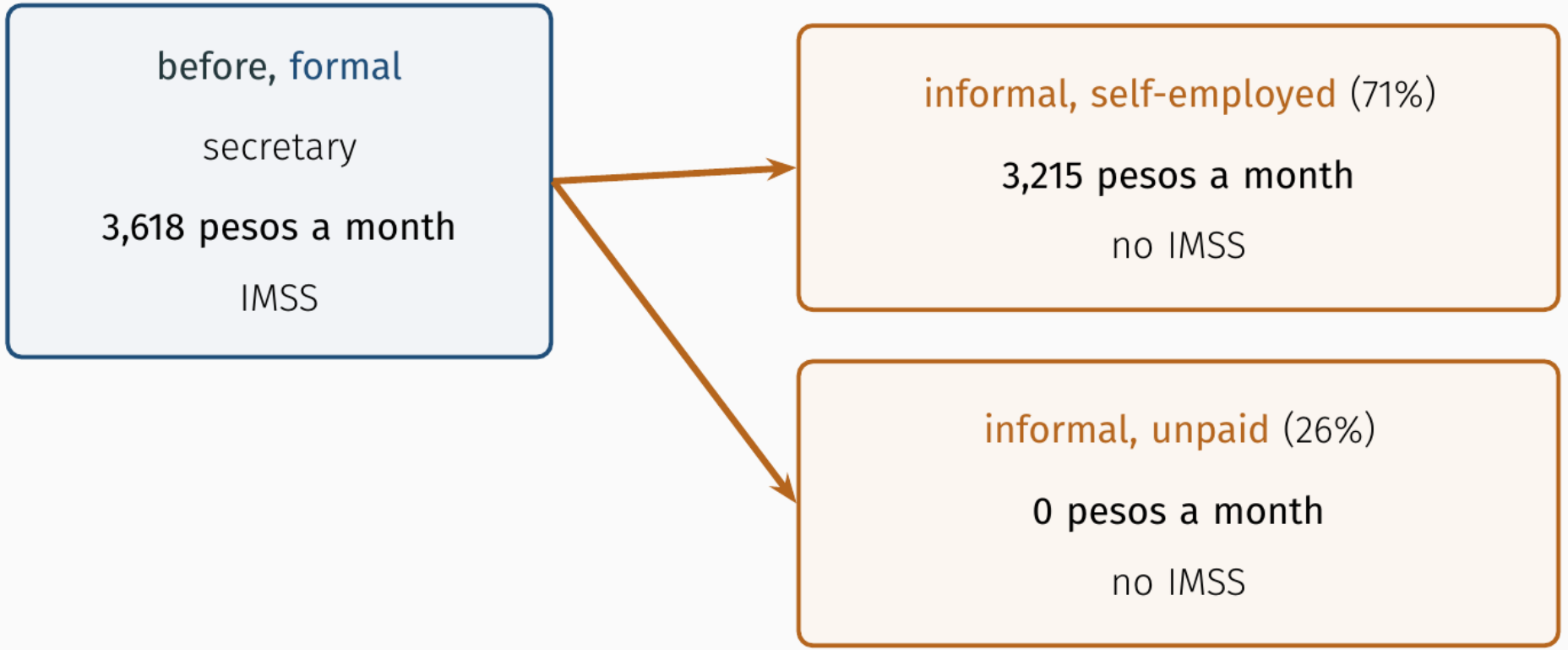
Who leaves for self-employment or unpaid work



Secretaries are the largest group leaving exposed formal clerical jobs; 64% of them are women.

Source: Composite of the 1,595 secretaries (SOC 43-6010) observed leaving a routine-exposed formal job for self-employment or unpaid family work, 2005–2019; origins over all such exits from clerical/retail jobs; weighted medians, 2005 pesos.

María goes informal: self-employed or unpaid

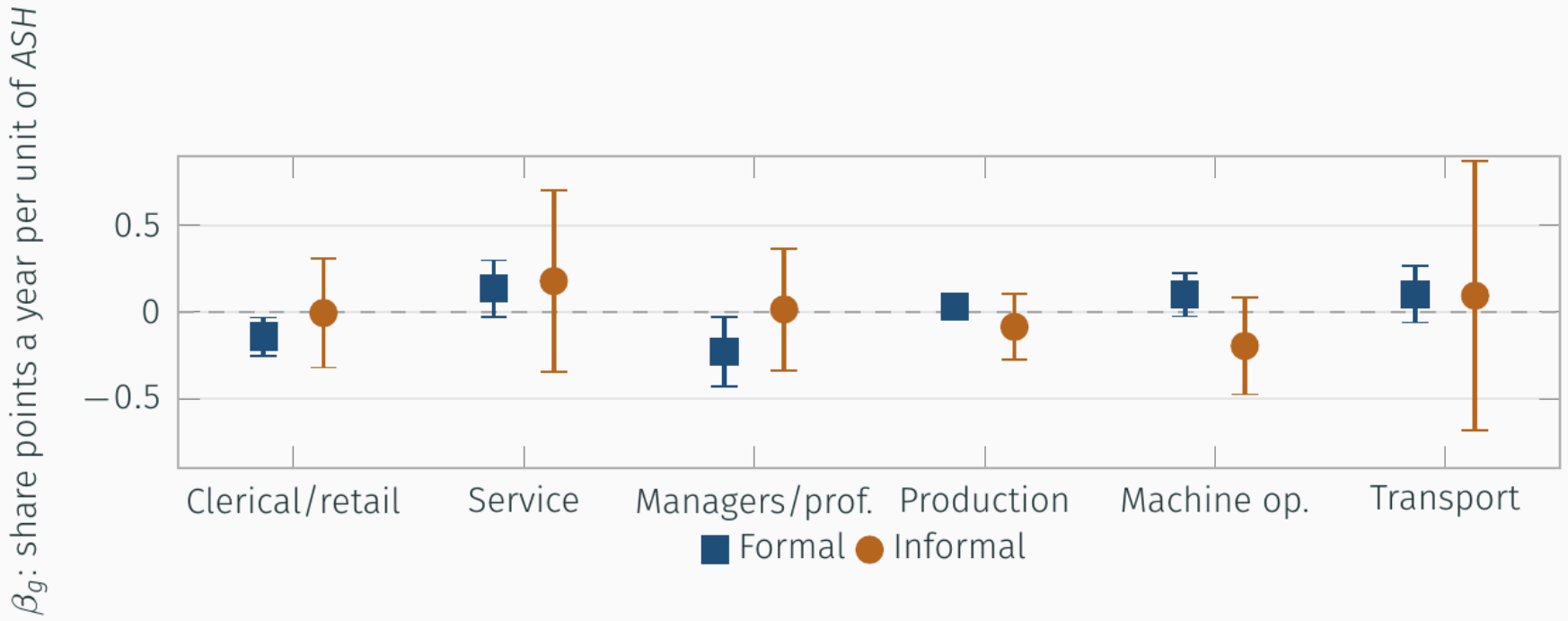


Informal either way.

Source: 1,595 secretaries (SOC 43-6010) moving from a routine-exposed formal job into self-employment (1,118) or unpaid family work (477), 2005–2019, weighted medians, 2005 pesos. Typical moves, not causal effects.

Early AI exposure falls on formal clerical and managerial jobs

$$\frac{OG_{g,\ell,t} - OG_{g,\ell,t_0}}{t - t_0} = \beta_g \, ASH_{\ell,t_0} + \delta_{S(\ell)} + \varepsilon_{g,\ell}, \qquad ASH_{\ell,t_0} \text{ instrumented by } Z^{AI}_{\ell} = \sum_i e_{\ell,i,t_0} \, A_{i,-s(\ell),t_0} \, g_{i,-s(\ell)}, \quad t_0 = 2022,\ t = 2025$$

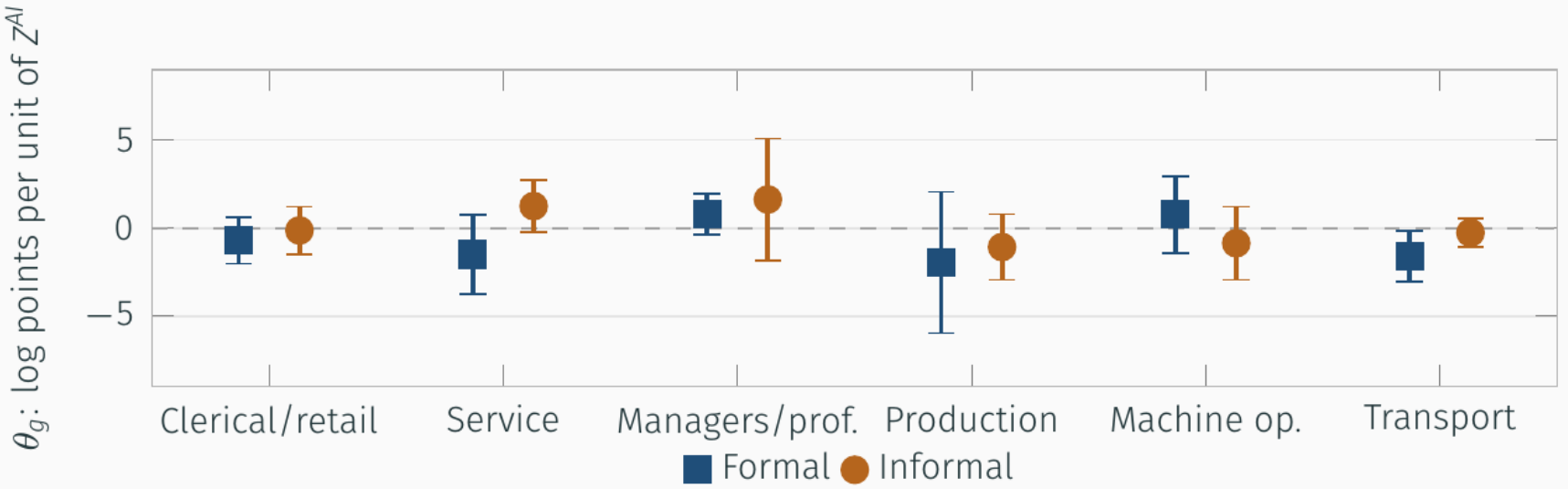


Formal (first-stage F 15.2): clerical/retail -0.142 (AR p 0.046), managers -0.228 (0.033). Informal first stage weak (F 3.3): nothing identified. ▸ GPT-5.6 classification

Source: LLMs 2022–25, by sector; Eloundou et al. GPT-4 task labels. ASH_{ℓ,t_0}: share of the sector's employment in occupations above the p66 mean T score; Z^{AI}_{ℓ}: 2022 3-digit industry shares × leave-out exposed share × leave-out 2022–25 growth; state FE, population weights, state-clustered 95% CIs. → tables → first stages

By sector, wage growth shows no clear response to AI exposure

$$\ln w_{n,y} = \sum_g \theta_g \, Z^{AI}_{\ell(n)} \, \mathbb{1}\{y = 2025\} \, \mathbb{1}\{g(n) = g\} + \mu_{\ell,k} + \mu_{S,k} + \mathbf{x}'_{n,y}\gamma_y + u_{n,y}, \qquad y \in \{2022, 2025\}$$



Formal clerical/retail θ_g = -0.705 (s.e. 0.673); informal -0.140 (0.690). Hiring margins: in progress.

▸ GPT-5.6 classification

Source: Worker-level reduced form on Z^{AI}_{ℓ} by group and sector, Eloundou et al. labels, as the routinization wage design; Z^{AI}_{ℓ} falls with exposure, so a positive θ_g is lower wage growth where exposure is higher; labor weights, LLM-clustered 95% CIs. → tables

What happens to María?

- Her job is exposed
- Formal jobs like hers shrink
- Her pay does not move
- Where she goes: open

Source: Secretaries (SOC 43-6010) score 0.62 on the Eloundou et al. labels, cutoff 0.42 (GPT-5.6: 0.73 vs 0.50); formal clerical/retail share -0.142 a year per unit of exposed share; formal clerical wage growth -0.705 per unit of Z^{AI}; informal first-stage F 3.3. Hiring margins: in progress.

The informal buffer protects wages and costs social protection

This paper	How it relates	Literature
Formal jobs shrink	*consistent with*	Brambilla et al. (2023)
Self-employment absorbs 64% of payroll jobs lost	*consistent with*	Dix-Carneiro and Kovak (2019) Ponczek and Ulyssea (2022)
	faster than	Dix-Carneiro and Kovak (2019)
Wages hold, IMSS lost	*consistent with*	Dix-Carneiro et al. (2026) Levy (2010)
	unlike	Dix-Carneiro and Kovak (2017)

Same shock, different margin.

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Exposure to Digital Technologies and Jobs in Global Value Chains

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Washington, DC, 18 November 2026

Digital technologies, production networks and employment

Technological change affects employment directly through productivity gains, displacement and new tasks, and indirectly through production networks and final demand.

Acemoglu and Restrepo (2019); Autor and Salomons (2018).

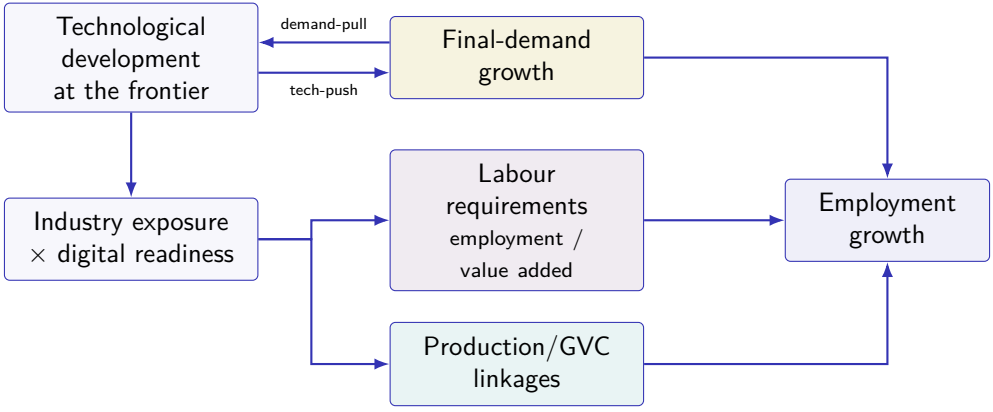
Our contribution

- Combine exposure to **9 digital emerging technologies** (Prytkova et al., 2025) with the employment-decomposition framework of Pahl et al. (2022).
- Distinguish **labour requirements from GVC-linkage contributions**, and compare **total employment with GVC jobs** to examine how different technologies relate to both channels across country-industries.

Research question

How does the emergence of digital technologies relate to employment changes through labour requirements and GVC linkages?

Framework: Technology, productivity, and production linkages



Employment growth has three accounting components: (i) final demand, (ii) labour requirements, and (iii) production linkages. We focus on the last two.

Final demand and frontier technological change affect one another, but worldwide final-demand growth is taken as given for an individual country-industry's technological exposure and digital readiness.

Three components of employment growth

$$\text{Employment}_{i,t} = E'_{i,t} \sum_j (V'_t B_t)_{ij} F_{j,t}, \qquad E'_{i,t} = \frac{\text{Employment}_{i,t}}{\text{ValueAdded}_{i,t}}, \quad V'_{i,t} = \frac{\text{ValueAdded}_{i,t}}{\text{GrossOutput}_{i,t}}.$$

$$\Delta \ln \text{Employment}_i = C_i^{\text{LR}} + C_i^{\text{GVC}} + C_i^{\text{FD}}, \qquad C_i^{\text{LR}} = \Delta \ln E'_i.$$

Labour requirements

$-$: higher value added per worker, possibly process innovation
$+$: lower value added per worker; new labour intensive tasks.

GVC linkages

$+$: increase in final demand share and supplier's importance.
$-$: less value added per unit of final demand: outsourcing and production reallocation.

Economic framework follows Pahl et al. (2022). Our log-change implementation averages the two polar paths, consistent with Dietzenbacher and Los (1998) and Miller and Blair (2009, ch. 13).

Data: OECD ICIO 2026 (CP/PYP); TiM 2025 (EMPN); ILOSTAT modelled employment (`EMP_2EMP_SEX_ECO_NB`).

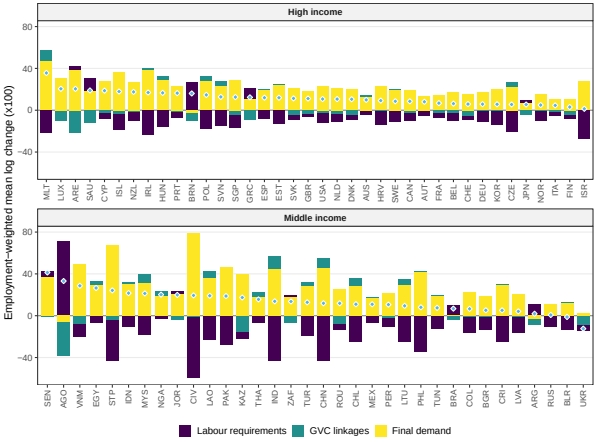
Employment changes and their components by country, 2012–2019

Final demand generally supports employment growth.

Lower labour requirements often offset part of that expansion.

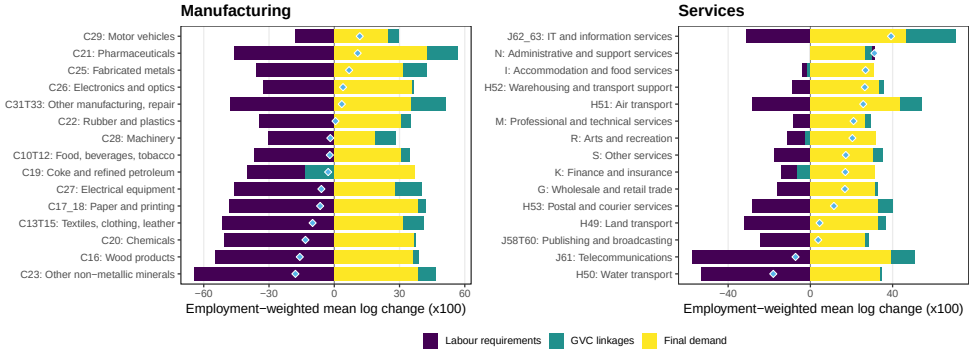
Linkage contributions vary across countries, becoming more important for GVC jobs.

GVC jobs descriptives



High-income countries above, upper- and lower-middle-income countries pooled below. Historical World Bank FY2012 groups. ROW excluded. Country means based on the p10-trimmed regression-sample industries; initial-employment-weighted log changes $\times 100$, not growth of aggregate employment.

Employment adjustment differs across manufacturing and services



Most manufacturing industries show lower labour requirements. Several services combine expanding final demand with positive linkage contributions.
Overall shift towards services from manufacturing.

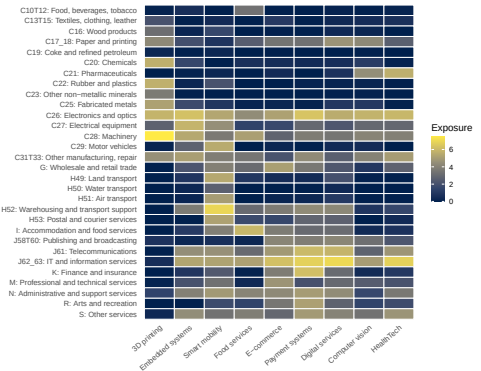
GVC jobs descriptives

2012–2019; 30 regression-sample industries; p10 trimmed; ROW excluded. Initial-employment-weighted mean log changes $\times 100$. Diamonds: observed mean log growth.

Technological exposure at the frontier

$$X_{if} = \text{TechExposure}_{if} \times \text{DigitalReadiness}_{c(i)}.$$

- Patent-text relevance of forty technologies to industry production.
- Nine families, following Prytkova et al. (2025).
- Digital readiness is proxied by fixed broadband subscriptions per 100 people, averaged over 2007–2011.



Frontier development, rather than observed adoption. Technologies adopted by suppliers or customers can also change production in the exposed industry. Details

Patent-based industry relevance: Prytkova et al. (2025). Digital-readiness proxy: World Bank WDI broadband, IT.NET.BBND.P2, 2007–2011.

Weighted regressions conditional on final demand

$$Y_i = \sum_{f=1}^{9} \beta_f X_{if} + \gamma C_i^{\mathrm{FD}} + \alpha_{c(i)} + \delta_{\mathrm{section}(i)} + \varepsilon_i.$$

Equation

Three outcomes: employment growth, labour requirements and GVC linkages. We do this for total employment and GVC jobs.

X_{if}: family-f exposure $\times$ digital readiness; nine families jointly.

γ: final-demand slope; α: country FE; δ: industry-section FE; ε: residual.

Estimation

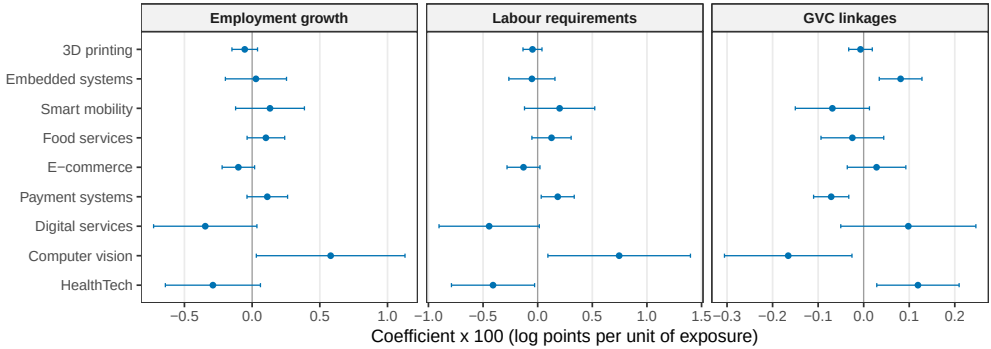
Non-primary, market industries: **C, G, H, I, J, K, M, N, R, S**.

We also estimate service and manufacturing specific relationship with interactions.

Initial employment weights; p10 size filter. Country/industry clustering; covariance repair when required.

Semi-elasticities: outcomes already in logs, exposures in levels. Same sample, weights and regressors imply $\beta_f^{\mathrm{Emp}} = \beta_f^{\mathrm{LR}} + \beta_f^{\mathrm{GVC}}$.

Non-primary industries: opposing labour and linkage contributions

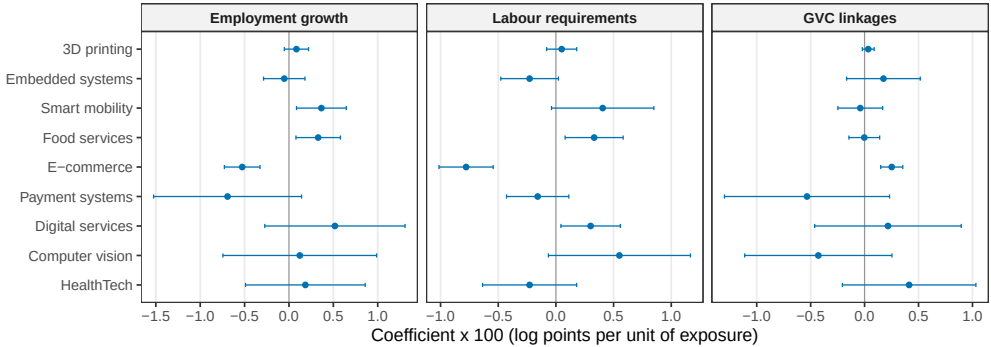


Labour requirements and GVC linkages often offset each other:

Computer vision and payments: higher labour requirements, lower linkages; only computer vision has a significant net association.

Digital services and embedded systems: lower labour requirements, stronger linkages, although coefficients are not always significant.

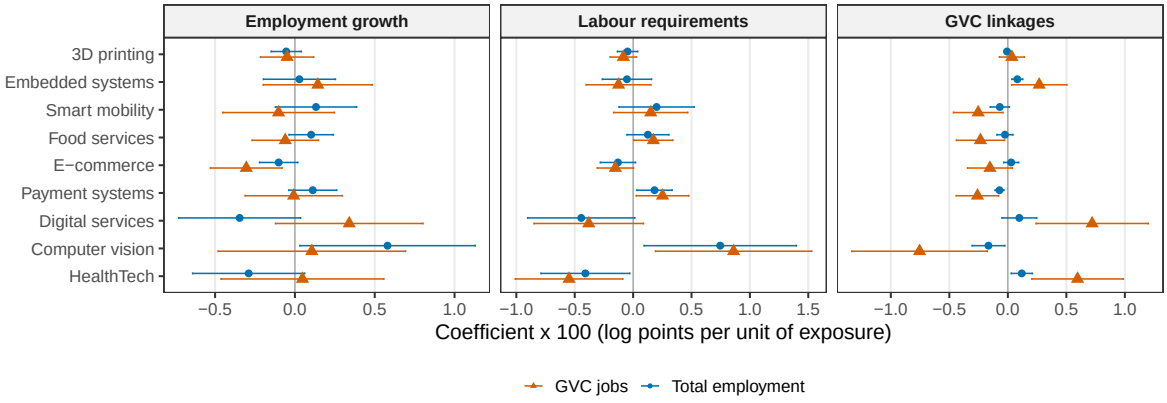
Manufacturing differs from services: labour adjustment matters



E-commerce: labour saving outweighs stronger linkages in manufacturing; no clear net services association.

Mobility and food services: clear positive manufacturing associations; services estimates are also positive but imprecise. Services comparison

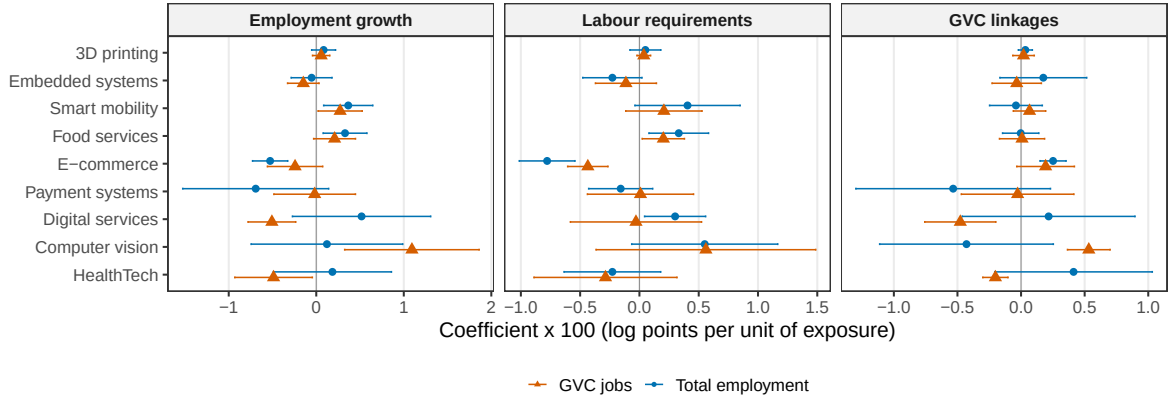
GVC jobs: similar pooled labour patterns, different linkages



Labour-requirement signs match across all nine families. GVC linkage coefficients are often larger in magnitude.

What are GVC jobs?

Manufacturing GVC jobs change the linkage story



Digital services: GVC-job linkages and employment turn negative.
Computer vision: GVC-job linkages and employment turn positive.
For these two tech production linkages, and employment, react differently when considering GVC linkages.

What are GVC jobs?

Conclusions

1. **Heterogeneity of technology and employment channels**. We provide a framework to account for this, which policy design should consider.
2. **Employment associations conceal opposing contributions.** Digital services' point estimates combine lower labour requirements and stronger linkages; computer vision shows the opposite pattern in market, non-primary industries.
3. **Manufacturing differs from the pooled result.** E-commerce shows a clear labour-saving employment contraction, while mobility and food services have positive net associations.
4. **GVC employment changes the production linkage pattern** for manufacturing. Digital services show negative linkages and employment; computer vision shows positive linkages and employment. Total-employment linkage estimates have the opposite signs.

Future research should combine direct adoption to distinguish underlying mechanisms.

Thank you

Questions and comments welcome

Filippo Bontadini, Tommaso Ciarli, Santiago Picasso and Maria Savona

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Data sources

Data

- OECD ICIO 2026, current and previous-year prices; OECD Trade in employment (TiM), 2025 edition, measure EMPN.
- ILOSTAT, *Employment by sex and economic activity – ILO modelled estimates*, `EMP_2EMP_SEX_ECO_NB`; extract dated 14 May 2025.
- World Bank WDI, fixed broadband subscriptions per 100 people (`IT.NET.BBND.P2`); historical income groups, FY2012.

Appendix: the three-way polar decomposition

1. Separate labour requirements. Since E_i' multiplies the whole value-added total,

$$\Delta \ln \text{Employment}_i = \underbrace{\Delta \ln E_i'}_{C_i^{\text{LR}}} + \Delta \ln (V'BF)_i.$$

2. Change linkages, holding final demand fixed. Average the log change at initial and final demand:

$$C_i^{\text{GVC}} = \frac{1}{2}\left[\ln \frac{(V_1'B_1F_0)_i}{(V_0'B_0F_0)_i} + \ln \frac{(V_1'B_1F_1)_i}{(V_0'B_0F_1)_i}\right].$$

3. Change final demand, holding linkages fixed. Average the log change at initial and final linkages:

$$C_i^{\text{FD}} = \frac{1}{2}\left[\ln \frac{(V_0'B_0F_1)_i}{(V_0'B_0F_0)_i} + \ln \frac{(V_1'B_1F_1)_i}{(V_1'B_1F_0)_i}\right].$$

Exact adding-up: $\Delta \ln \text{Employment}_i = C_i^{\text{LR}} + C_i^{\text{GVC}} + C_i^{\text{FD}}$.

Subscripts 0 and 1 denote consecutive years at common prices. Average the two opposite-order paths; sum annual contributions over 2012–2019. Dietzenbacher and Los (1998); Miller and Blair (2009, ch. 13).

Appendix: why average the two polar paths?

Both linkages and final demand change. Which should change first?

Calculate a country-industry's value added under all four combinations:

	Initial demand F_0	Final demand F_1
Initial linkages $V_0' B_0$	60	65
Final linkages $V_1' B_1$	72	80

Linkages first: $60 \to 72 \to 80$. **Demand first**: $60 \to 65 \to 80$.

Average the linkage change along both paths: $C^{\mathrm{GVC}} = \frac{1}{2}[\ln(72/60) + \ln(80/65)] = 0.1950$.

Average the demand change along both paths: $C^{\mathrm{FD}} = \frac{1}{2}[\ln(65/60) + \ln(80/72)] = 0.0927$.

Their sum is exactly $\ln(80/60) = 0.2877$. Add $\Delta \ln E'$ to obtain employment log growth.

Illustrative numbers. Opposite-order averaging: Dietzenbacher and Los (1998); Miller and Blair (2009, ch. 13). No LMDI cell weights are used.

Appendix: common prices and the logarithmic identity

Within each annual comparison, we evaluate both dates at the same prices: initial-year current prices and final-year previous-year prices.

Each polar path adds up to the same value-added log change:

$$\ln \frac{(V_1' B_1 F_0)_i}{(V_0' B_0 F_0)_i} + \ln \frac{(V_1' B_1 F_1)_i}{(V_1' B_1 F_0)_i} = \ln \frac{(V_1' B_1 F_1)_i}{(V_0' B_0 F_0)_i}.$$

Labour requirements separate without weights because E_i' multiplies the entire row total:

$$\Delta \ln \mathrm{Employment}_i = \Delta \ln E_i' + \Delta \ln (V' B F)_i.$$

Chain the seven annual contributions to obtain 2012–2019 changes.

Inventories are retained. Matrix-vector products are computed before taking logs. Individual zero or negative cells are not replaced by small positive values.

Appendix: total employment and GVC jobs

$$\text{Employment} = \text{diag}(E')\, V'BF, \qquad \text{GVCJobs} = \text{diag}(E')\, V'\widehat{B}F.$$

$\widehat{B}$ equals B with its within-country blocks set to zero. The GVC measure retains links to foreign country-industry columns.

Two-country illustration

With $E' = (8, 4)$, $V' = \text{diag}(0.4, 0.6)$, $F = (100, 100)'$ and

$$B = \begin{bmatrix} 1.75 & 0.25 \\ 0.50 & 1.50 \end{bmatrix}, \qquad \text{diag}(E')V'B\,\text{diag}(F) = \begin{bmatrix} 560 & 80 \\ 120 & 360 \end{bmatrix},$$

total jobs are $(640, 480)'$, while the retained foreign-block jobs are $(80, 120)'$.

Back to results

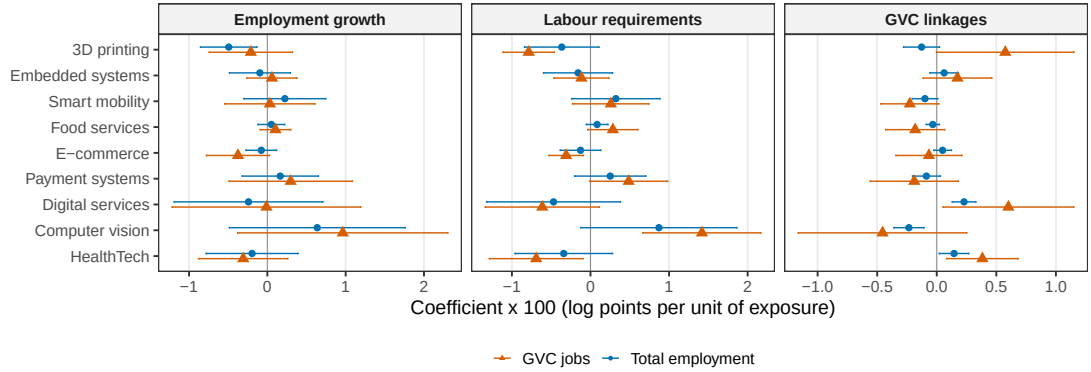
Appendix: nine families and their detailed technologies

3D printing	Printer hardware, 3D printing, additive manufacturing
Embedded systems	Smart agriculture and water, IoT, energy management, industrial automation, remote monitoring, smart home
Smart mobility	Logistics, autonomous vehicles, parking, telematics, passenger transport
Food services	Food ordering and vending systems
E-commerce	Advertising, trading and auctions, online shopping, coupons
Payment systems	Electronic payments, mobile payments, gaming and wagering
Digital services	Authentication, e-learning, location services, voice, messaging, workflow, cloud storage, information processing, cloud computing, recommenders, social networking, digital content
Computer vision	AR/VR, machine learning and neural networks, medical imaging
HealthTech	Health monitoring, medical information, e-healthcare

Prytkova et al. (2025). The classification combines heterogeneous uses. Computer vision is not a comprehensive measure of all AI technologies.

Back to main slides.

Appendix: services, total and GVC employment

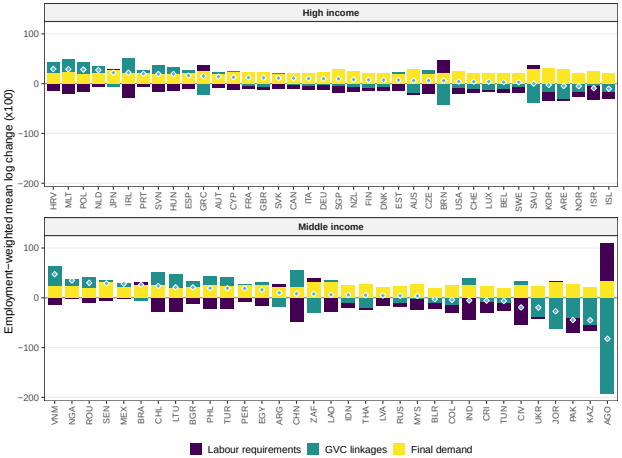


Digital services and HealthTech have positive linkage coefficients in both scopes. Most services net-employment coefficients are imprecise.

Weighted polar tech9 FE, 26 October 2026. Absolute services slopes from sector interactions. GVC 3D printing has a negative labour-requirement contribution, but an imprecise net association.

Back to manufacturing results

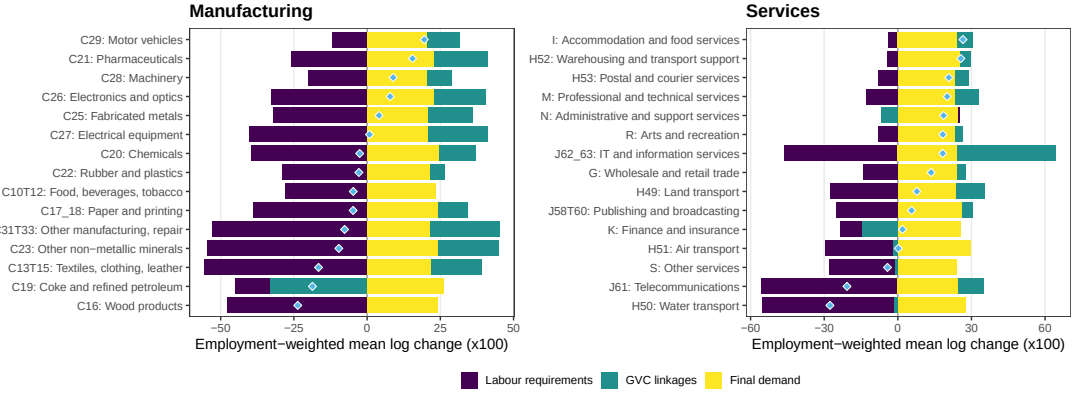
Appendix: GVC employment descriptives by country



Initial-employment-weighted mean cell log changes $\times 100$; p10 trimmed; not aggregate country growth.

Back to total employment

Appendix: GVC employment descriptives by industry



Initial-employment-weighted mean cell log changes $\times 100$; p10 trimmed; not aggregate industry growth.

Back to total employment



AI and Implications for EMDEs

David Kaplan, Inter-American Development Bank

November 18, 2026

Comments from an AI skeptic on “The Informal Buffer”

- Important because it addresses some simple, basic questions

  Is the AI really displacing workers in EMDEs?

  What happens to displaced (unemployment, informality) workers?

- Very convincing evidence that AI is having an impact on the Mexican labor market, displacing workers into informality

- Many important questions remain

  Is AI a bigger shock than earlier shocks? Policy implications?

Comments on “Disruption without Dividend?”

- The main contribution is not to tell us how AI will affect the labor market

  The statement that “the aggregate implications for labor demand, job quality, and earnings distribution remain highly uncertain” continues to be true

- The detailed nature of the analysis is the main contributions because it puts new policy issues on the table

- A huge improvement over papers that say “X% of jobs are exposed”

How can there be any policy implications under such uncertainty?

- It’s probably dangerous to aggressively pursue policies that are only useful if the models or simulations are right
- Safer to prioritize policies that will be helpful even if the models or simulations are wrong, but even more important if they’re right
- Example: If Acemoglu and Restrepo are right about the danger of “so-so technologies”, we should stop taxing capital less than labor

  A lot of us were advocating for that before AI

I have some new fears of AI

- What if EMDEs experience the labor replacement of AI, but lack the digital infrastructure to capitalize on the labor augmentation effects?
- Improving the digital infrastructure of EMDEs is probably a good idea regardless of AI, but may be crucial if the authors are right
- Also, AI might “attack” office-based occupations, representing a disproportionate share of the “good” skilled jobs in EMDEs
- What should we do about that?

Comments on “Exposure to Digital Automation and Jobs in Global Value Chains”

- Paper reminds us that AI adoption happens in the context of global markets

  I can automate (replace workers with AI), or I can offshore labor, I can reshore by substituting foreign labor with domestic capital

- In general, this is the paper that takes equilibrium effects most seriously

- It also has some results that coincide with my AI skepticism

Should looking at equilibrium effects assuage concerns?

- Three types of effects:

  1. Productivity driver: changes in the labor intensity of production
  2. GVC linkage driver: changes in the sourcing structure of intermediate inputs
  3. Final demand driver: changes in the scale of global consumption of final product affecting employment across country-industries participating in GVCs.

- “Final demand and productivity most often offset each other”

Do we need radically new policies?

- Maybe what we need is to really advance on policy recommendations we have had for a long time

1. Correct labor market distortions that could lead to technology displacing labor despite not being more productive
2. Ensure country-wide access to digital technologies
3. Strengthen skills formation policies, ensuring access to vulnerable populations
4. Strengthen mechanisms for protecting people who need to transition to new jobs (unemployment insurance, for example)